View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Clemson University: TigerPrints

Clemson University

TigerPrints

All Dissertations

Dissertations

December 2019

Modeling of Household Evacuation Decision, Departure Timing, and Number of Evacuating Vehicles from Hurricane Matthew

Roa'a Jaber Mohammad Alawadi

Clemson University, ruaa.jaber92@gmail.com

Follow this and additional works at: https://tigerprints.clemson.edu/all_dissertations

Recommended Citation

Alawadi, Roa'a Jaber Mohammad, "Modeling of Household Evacuation Decision, Departure Timing, and Number of Evacuating Vehicles from Hurricane Matthew" (2019). *All Dissertations*. 2522.
https://tigerprints.clemson.edu/all_dissertations/2522

This Dissertation is brought to you for free and open access by the Dissertations at TigerPrints. It has been accepted for inclusion in All Dissertations by an authorized administrator of TigerPrints. For more information, please contact kokeefe@clemson.edu.

MODELING OF HOUSEHOLD EVACUATION DECISION, DEPARTURE TIMING, ANDNUMBER OF EVACUATING VEHICLES FROM HURRICANE MATTHEW

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Civil Engineering

---

by
Roa'a Jaber Alawadi
December 2019

Accepted by:
Dr. Pamela Murray-Tuite, Committee Chair
Dr. Jennifer H. Ogle
Dr. Wayne A. Sarasua
Dr. Abdul A. Khan

ABSTRACT

This dissertation investigates households' evacuation decision, number of household vehicles used in evacuation, and departure timing from Hurricane Matthew. Regarding the evacuation decision, this dissertation takes a step further by presenting three level evacuation decision models that include full, partial, and no evacuation alternatives rather than the binary evacuate/stay decision. Multinomial (MNL) regression and random parameter MNL techniques were utilized to develop the prediction models. Results showed that some of the variables which affect the evacuate/stay decision have different influences on the three alternatives. The preferred MNL model was tested for random parameters and one random parameter (age of the respondent) was identified for the utility expression pertaining to the no evacuation alternative.

For the vehicle choice study, zero truncated Poisson regression was utilized with the survey data. This modeling approach has rarely been applied to the evacuation context and the prediction of the number of household vehicles used is relatively understudied, compared to other evacuation-related decisions. The final preferred model contains three significant variables (marital status, gender, and evacuation timing from 6 am to noon).

The final part of this dissertation investigates the factors affecting departure timing choice. Having an accurate estimate of the departure time will allow the prediction of dynamic evacuation demand and developing effective evacuation strategies which will enhance the overall evacuation planning and management. A Cox proportional-hazards model was utilized to model the evacuation departure timing. Four significant variables

were identified in the final model, two of them are related to uncertainty. This part of the dissertation also studies evacuees' stated preference about whether or not they would change their evacuation timing if they relived the hurricane event. In our study, almost 34% of respondents reported that they would change their departure timing if they relived the hurricane event. A binary logit model was utilized in this part and the preferred model contains five significant variables related to past experience, the type of evacuation order received, and the evacuation destination.

DEDICATION

This dissertation is dedicated to my parents Amina and Jaber Alawadi for their endless love and support throughout my whole life. Without their loving support, I could not have made it this far. Words cannot express my feelings and gratitude.

I would like also to dedicate this dissertation to my supportive Husband Ahmad Tarawneh for his support and his love. In addition, I would like to dedicate this dissertation to the newest member in my family; my beloved son Zaid. I love you all.

ACKNOWLEDGMENTS

First and foremost, I would like to thank Allah for giving me the opportunity, hope, strength, and patience to complete this dissertation. Without his blessing, this work would not have been completed.

I would like to thank and acknowledge my advisor Dr. Pamela Murray-Tuite for her continuous guidance, patience, and support throughout my study. Her guidance improved the quality of my research and led to writing this manuscript. In addition to my advisor, I would like to thank my committee members Dr. Jennifer H. Ogle, Dr. Wayne A. Sarasua, and Dr. Abdul A. Khan for their helpful comments and guidance.

I would like to thank all the contributors in this research including all the professors and student colleagues in the HSEES project for their guidance and contribution throughout this study.

Furthermore, I would like to thank the National Science Foundation for supporting this project grant CMMI-1520338 "Hazards SEES: Bridging Information, Uncertainty, and Decision-Making in Hurricanes using an Interdisciplinary Perspective."

Last but not least, I would like to thank my parents and my husband for believing in me and supporting me to achieve my dream.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Research Motivation

Evacuation is a protective action that involves people moving from a threatened area to a safer area (Lindell et al. 2019). Evacuation goals include avoiding injuries, loss of life, and lower property damage and economic loss. This is why a main objective of evacuation is to move the evacuees from the danger zone as quickly and safely as possible (Lindell et al. 2019). Hurricane evacuation research is becoming increasingly important since hurricanes are considered among the deadliest natural hazards, with an increase to 116 in the average annual fatalities between 2001 and 2010 (National Oceanic and Atmospheric Administration (NOAA) 2011). The importance of hurricane evacuation research arises from the continuous population growth on both the Atlantic and Gulf coasts, the inability of the transportation infrastructure to keep up with this growth (Dow & Cutter 2002), and the high cost associated with these hazards (National Hurricane Center (NHC) 2006).

With the rise in population and the infrastructure constraints, evacuation demand models would benefit from greater resolution, such as considering full, partial, and no household evacuation, as well as better estimation of the number of household evacuating vehicles and the departure timing of the evacuating households. The ability to predict the characteristics and number of evacuees and vehicles and when these households would depart facilitates managing the evacuation process. Being trapped on highways during the hurricane could result in deaths due to storm surge in some areas (Lindell et al. 2005).

During an evacuation process, households make a series of evacuation-related decisions: whether to evacuate or not, when to evacuate, where to evacuate, which mode to use, and the number of vehicles to use in the evacuation, among other decisions. This decision making process is complex in nature and it is important to understand the factors influencing these decisions so that emergency management agencies can develop and implement successful hurricane evacuation plans. This dissertation focuses on three main decisions: (1) whether and how much of the household evacuates, (2) for the households who evacuate at least partially, how many household vehicles are used to evacuate, and (3) the departure timing of the evacuating households and households' intention to change this timing if they relived the event.

1.2 Hurricane Matthew Overview

Hurricane Matthew was a category 5 Atlantic hurricane (on the Saffir-Simpson Hurricane Wind Scale) that later made landfalls as a major hurricane along the coasts of southwestern Haiti, extreme eastern Cuba, and western Grand Bahama Island, and as a category 1 hurricane along the central coast of South Carolina (Stewart 2017). Hurricane Matthew is considered the lowest latitude hurricane to ever reach category 5 intensity in the Atlantic Basin (Stewart 2017). The maximum storm surge measured by a tide gauge in the United States was 7.70 ft above normal tide levels at Fort Pulaski, Georgia. It also produced storm surges of 6.96 ft at Fernandina Beach, Florida, 6.20 ft at Charleston, South Carolina, and 6.06 ft at Hatteras, North Carolina. This hurricane is considered one of the deadliest Atlantic storms since Katrina in 2005 and led to one of the largest recent hurricane evacuations along the Southeastern coast of the United States (Martín et al. 2017). It was responsible for 585 direct deaths. Of which, more than 500 deaths occurred in Haiti, and 34 in the United States (Stewart 2017).

The Jacksonville, Florida metropolitan area is centered on the banks of the St. Johns River in the First Coast region of northeast Florida. It is the fourth largest metropolitan in Florida (FL

Hometown Locator 2019). Jacksonville was one of the areas severely affected by Hurricane Matthew, where it became a category 2 hurricane east-northeast of Jacksonville Beach, Florida ((Stewart 2017). The hurricane caused major sand dune damage and flooding in the St. Johns River, it also destroyed many properties and caused power outage for nearly 250,000 electrical customers (Stewart 2017).

1.3 Goals and Objectives

The main goal of this dissertation is to provide models that help in better understanding and predicting of human behavior during evacuations, thus enhancing the overall demand modeling and evacuation planning and operations. The objectives of studying the three alternative (full, partial, no) evacuation decision are to identify the factors associated with selecting each alternative and determining whether factors from the literature associated with a binary evacuate/stay choice are more nuanced than previously believed. Another objective of this dissertation is to improve the overall evacuation vehicle demand estimation by identifying factors associated with models for and better prediction of the number of evacuating vehicles and evacuation departure timing. Finally, this dissertation aims to test the effect of uncertainty on the evacuating households during the evacuation process, and introducing uncertainty as a new, possible influencing factor on the evacuation decision and logistics.

1.4 Full and Partial Household Evacuation Decision

Over the past several decades, considerable research studies focused on factors affecting the hurricane evacuate/stay decision of residents (C. Gladwin, Gladwin & Peacock 2001). Such factors include household socio-economic and demographic factors (age, gender, ethnicity, education, etc.). Other factors affecting the hurricane evacuate/stay decision include hurricane characteristics (path, intensity, etc.) and emergency management practices (mandatory or voluntarily evacuation notice) (Solis, Thomas, & Letson, 2010).

This dissertation contributes to the hurricane evacuation research by accounting for partial household evacuation and the utilization of random parameters in the prediction models, which allow mixed parameter effects. Accounting for partial household evacuation helps to better understand complex human behavior and could lead to better evacuation predictions. Random parameters multinomial logit (MNL) models are used to account for three alternatives of full, partial, and no household evacuation and the heterogeneity of parameters across households in a sample of Jacksonville, Florida residents' responses to Hurricane Matthew. New variables, such as certainty about hurricane characteristics, are also considered in this study. Additional factors investigated include information on the household socioeconomic and demographic characteristics, home ownership and residence type, and past hurricane experience.

1.5 Household Number of Vehicles Used In Evacuation

The second main focus of this dissertation is to better understand the factors affecting household choice of the number of household vehicles used in evacuation. This will allow a better prediction of the number of evacuating vehicles; and thus a better overall evacuation vehicle demand estimation. Personal vehicles are by far the most preferred evacuation mode of transportation (Lindell et al. 2019). Many research studies presented a relatively wide range of the number of household vehicles used in evacuation. For example, Lindell et al. (2011) reported a range of (1.10 – 2.15) vehicles used by households across counties for Hurricane Lili. When taking into account the total number of evacuating households, this range allows for a huge difference in the predicted number of vehicles, which makes providing a better predicting model a necessity.

This study tests potential factors affecting household vehicle choice, taking into account socio-economic and demographic factors, living in a risk area, receiving evacuation notices, housing type, past hurricane experience, evacuation timing, family cohesion, hurricane information certainty, and whether household members evacuated partially or fully. Data for this study also comes from a survey of Jacksonville, Florida residents after Hurricane Matthew. Survey responses show that the majority of respondents used personal vehicles in evacuation; only five respondents reported using other modes of transportation. Zero truncated Poisson regression was utilized to model the number of household vehicles used for evacuation along with the significant predictors of the vehicle choice.

1.6 Departure Timing and Departure Timing Learning Experience

This dissertation also examines both the factors affecting evacuation departure time choice for Hurricane Matthew and the factors associated with whether the evacuees anticipate changing their departure time for a future hurricane. The choice of departure time during disasters is a complex dynamic process and depends on the risk that the hazard represents, the characteristics of the household, and the built environment features (Hasan et al. 2013). Factors studied in this part include socio-economic and demographic factors, living in a risk area, receiving evacuation notices, housing type, past hurricane experience, evacuation timing, family cohesion, hurricane information certainty, and the number of vehicles used in evacuation. Family cohesion and certainty variables are new factors to be considered in such studies. Family cohesion is related to the household agreement and satisfaction in decision making and uncertainty in this context relates to the timing and location of hurricane impact and the details of the household evacuation (e.g., destination, preparation time, route, etc.) A Cox proportional-hazards model was utilized to model the evacuation departure timing and identify the significant predictors of the departure timing.

The second part of the study presents the effect of households' recent hurricane experience on their anticipated consistency of departure timing for future hurricanes. Consistency would support assumptions of transferability of results from one event (in a given location) to the next, whereas anticipated changes could inform departure time range assumptions for simulation of future events. A binary logit model was used to study the binary choice of making a change in the departure timing if they relived the hurricane event or not.

1.7 Dissertation Organization

The remainder of the dissertation contains five chapters. Chapter 2 provides a review of the literature on household evacuation decisions and the studies about households vehicles usage for evacuation. Chapter 3 presents a paper manuscript titled Modeling Full and Partial Household Evacuation from Hurricane Matthew with A Mixed Multinomial Logit Model. This paper was submitted to *Transportation Research Part D*. Chapter 4 presents a second paper manuscript titled Modeling Number of Household Evacuating Vehicles from Hurricane Matthew With A Truncated Poisson Model. This paper was accepted for presentation in Transportation Research Board (TRB) annual meeting 2020. Chapter 5 presents the third paper manuscript titled Determinants of Departure Timing For Hurricane Matthew and Anticipated Changes For A Future Hurricane; this paper is to be submitted shortly. Chapter 6 summarizes and concludes the dissertation by identifying the major contributions.

1.8 References

Dow, K. and Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natural hazards review, 3(1), pp.12-18.

"Florida Metropolitan & Micropolitan Statistical Areas". FL Hometown Locator. Retrieved March 11, 2019.

Gladwin, C.H., Gladwin, H. and Peacock, W.G., 2001. Modeling hurricane evacuation decisions with ethnographic methods. International Journal of Mass Emergencies and Disasters, 19(2), pp.117-143.

Lindell, M.K., Kang, J.E. and Prater, C.S., 2011. The logistics of household hurricane evacuation. Natural hazards, 58(3), pp.1093-1109.

Lindell, M.K., Lu, J.C. and Prater, C.S., 2005. Household decision making and evacuation in response to Hurricane Lili. Natural Hazards Review, 6(4), pp.171-179.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. and Baker, E.J., 2019. Large-scale evacuation. New York: Routledge.

Martín, Y., Li, Z. and Cutter, S.L., 2017. Leveraging Twitter to gauge evacuation compliance: Spatiotemporal analysis of Hurricane Matthew. PLoS one, 12(7), p.e0181701.

National Hurricane Center (NHC). (2006). "Tropical cyclone report: 2005 Atlantic hurricane season." National Oceanic and Atmospheric Administration (NOAA), Washington, DC

National Oceanic and Atmospheric Administration (NOAA). (2011).

Petkar, Sofia. "Hurricane Matthew is the 'most dangerous storm in living memory'". Metro. UK. Retrieved October 8, 2016.

Solís, D., Thomas, M. and Letson, D., 2010. An empirical evaluation of the determinants of household hurricane evacuation choice. Journal of Development and Agricultural Economics, 2(5), pp.188-196.

Stewart, S.R., 2017. National Hurricane Center Tropical Cyclone Report: Hurricane Matthew. AL14016. National Oceanographic and Atmospheric Administration (NOAA).

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Evacuation modeling is a broad and very active research field. Among the most significant advances over the past four decades is the development of quantitative modeling of the evacuation process (Lindell et al. 2019). Several papers provide relatively comprehensive literature reviews for different branches of the evacuation modeling. This dissertation studies the household evacuation decision, vehicle usage, and departure timing. A large body of work focuses on identifying which households would evacuate or not as well as developing empirical modeling of evacuation departure timing. However households' vehicle usage choice rarely has been rigorously modeled for evacuations, neither developing behavioral models for understanding the factors affecting departure timing choice (Yin et al. 2014).

The subsequent sections discuss the previous research efforts that are closely related to this dissertation. Specifically, the literature review is organized according to the different evacuation decisions identified in the previous chapter. First, the studies on partial and full household evacuation will be discussed in Section 2.2, Section 2.3 will introduce previous research about household vehicle choice in evacuation, section 2.4 will discuss previous studies of evacuation departure timing, and finally section 2.5 discusses the gaps of previous studies and the role of this dissertation in filling them.

2.2 Full and Partial Household Evacuation Decision

A number of evacuation predictors were previously studied, such as perceived risk, warnings, official evacuation notices, environmental and social cues, information sources, past experience, housing type, pet ownership, and demographic characteristics (Lindell et al. 2019).

It would be reasonable that people who believe they are in danger are more likely to evacuate in order to reduce the danger of the hazardous event (Lindell et al. 2019). There are at least two components to perceived risk, belief that one will experience the hazardous event, and the belief that one will be adversely affected by it (Lindell et al. 2019). Previous hurricane evacuation studies have rich insights about risk perception and its relationship to evacuation. Perry et al. (1981) reported results of surveys in four communities that experienced riverine flooding in the western United States. If residents heard that the water was rising or the flooding may cause possible danger, 36% evacuated. If they heard that the flood was occurring and the water was approaching their location, 66% evacuated. Of the residents who somehow did not believe the danger, 16% evacuated. Compared to 59% who largely believed the flood warning. Of those who believed their personal risk from the flood was slight, 24% evacuated versus 87% who said that their personal risk was severe.

Quarantelli (1980) showed that the characteristics of the received warning messages including credibility, frequency and specificity were significant factors affecting the decision to evacuate or not. Baker (1991) added that how residents obtained risk information was a major factor affecting the evacuation decision. Warning response varies with warning source, content, the number of warnings received and the belief of the warning itself (Mileti et al. 1975). Responses to warnings are also influenced by the sender and receiver characteristics (Sorenson & Vogt-Sorenson 2006). However, Dow & Cutter (1998) suggest that the household evacuation decision is affected more by media and household characteristics than the actual warning.

As a predictor of evacuation, environmental cues refer to conditions that people can observe in their physical environment that indicates the presence of threat (e.g., rising water, a very heavy rainfall that may cause flash floods, high wind speed). White (1978) reported that people at the mouth of Colorado’s Big Thompson Canyon refused to evacuate when given an accurate flash flood warning because the morning sky was clear and sunny. However, they later evacuated when they were inaccurately warned of a dam break upstream in East Park because the dam break is not expected to provide environmental cues before the flood water arrived.

Factors such as socio-economic and demographic variables are not good predictors of evacuation (Lindell et al. 2019). Literature also has mixed results of other factors such as information sources. For example, Dow and Cutter (2000, 2002) showed that coastal residents have many risk information sources other than the information issued by official sources.

Previous hurricane experience has mixed effects on hurricane evacuation since the role of evacuation experience is not as straight forward as it may seem. Recent literature reviews found no consistent relationship between evacuation and experience (e.g., Huang et al. 2016; Thompson et al. 2017). Some studies found positive relationships, some found negative relationships, but most found no relationship. Huang et al. (2016) found that among 21 studies of household evacuation, 24% reported significant positive correlations, 10% reported significant negative correlations, and 66% reported nonsignificant correlations.

Pet ownership is another evacuation predictor with small or nonsignificant effects on the overall evacuation (Hunt et al. 2012). Studies have compared evacuation rates between people who did and did not own pets. Thompson et al. (2017) found pet owners to be less likely to evacuate since many pet owners are reluctant to evacuate if they cannot take their pets with them. If the available evacuation accommodation does not allow pets, this provides a deterrent to evacuation (Heath, Beck et al. 2001).

Housing type is one of the best predictors of evacuation (Huang et al. 2016). For example, mobile home and manufactured home residents are usually deemed to be more vulnerable than site built housing to wind and storm surge (Lindell et al. 2019). Mobile home residents generally recognize their greater risk and are therefore more likely to evacuate than site-built home residents.

2.3 Number of Household Vehicles Used in Evacuation

There are three main travel modes used in large scale evacuations: personal vehicles, carpooling and official transportation (school buses or transit agencies) (Lindell et al. 2019). In some cases, the governments used aircraft, postal vehicles, trains, or even fire trucks for very localized flooding (Perry et al. 1981). However, personal vehicles are the dominant mode of transportation used in large scale evacuations in the United States. Vehicle usage choice rarely has been strictly modeled for evacuations (Yin et al. 2014). Based on the limited prior surveys, percentages of personal vehicle usage in hurricane evacuation are 90% in Hurricane Lili (Lindell et al. 2011), 89% in Hurricane Katrina (Wu et al. 2012), and 87% in Hurricane Ike (Wu et al. 2013). Even though existing research emphasizes having the household together during evacuations, this does not necessarily mean that households will evacuate in one vehicle (Dow and Cutter 2002). According to Dow and Cutter (2002), 25% of households used multiple vehicles in evacuation. Households used an average of 1.26 vehicles to evacuate from Hurricane Floyd (Dow and Cutter 2002), 1.42 vehicles in Katrina/ Rita (Wu et al. 2012), and 1.25 vehicles in Ike (Wu et al. 2013). Lindell et al. (2011) reported a range of 1.10 – 2.15 vehicles across counties for Hurricane Lili. The wide range of vehicles usage in hurricane evacuation is problematic for evacuation planners, with a difference of over 1 million vehicles in an evacuation of 1 million households (Yin et al. 2014).

Public transportation has low usage in evacuations: an estimated 13% in four flood evacuations (Prater et al. 1981) and 1% in Hurricane Lili, less than 1% in Katrina/ Rita, and 1% in Ike (Lindell et al. 2019). This big difference in percentages of public transportation use in evacuation is due to longer evacuation distances in hurricane evacuations than flood evacuations (Lindell et al. 2019).

The predictors of the number of household evacuating vehicles were studied in a few prior works. It was found that larger households and those with more income took more cars (Dow and Cutter 2002). Wu et al. (2012) reported that married households took more vehicles in the evacuations for Hurricanes Rita and Katrina. Similarly other factors, such as hurricane experience and receiving mandatory evacuation orders, were found to have a positive effect on household usage of vehicles in evacuation (Yin et al. 2014). Dow and Cutter (2002) provided reasons for households using more vehicles in evacuation. It could be explained by job responsibilities that might require one household member to return sooner than others, or residents took many possessions with them, or they want the flexibility to allow one member to return to cleanup while others stay with children. Other indicators of car usage in evacuation along with their effects are presented in Chapter 4.

2.4 Departure Timing and Departure Timing Learning Experience

Most of the previous studies on departure timing focused on deriving empirical distributions without considering the influences of different factors (Hasan et al. 2013). These empirical distributions describe the rate of vehicles' entry to the emergency planning network (Yin, 2013). The response curves present the percentage of departures at every time interval of the planning horizon (Pel et al. 2012). A variety of shapes were assumed for the departure time distributions. For example, the sigmoid curve is among the widely accepted distributions (Radwan et al. 1985). Other assumed departure timing distributions are listed in Chapter 5.

The cumulative distribution of warning times and preparation times can be combined, theoretically, to produce a normalized distribution of departure times; however, practical limitations exist (Lindell, Murray-Tuite at al. 2019). Lindell, Murray-Tuite et al. (2019) stated that in practice, it can be quite challenging to construct a household distribution of departure time from the available data of warning receipt and evacuation preparation because some households evacuate before they receive an official evacuation notice. Also, constructing a synthetic departure distribution from warning diffusion and preparation time distributions requires an assumption about the correlation between warning receipt and evacuation preparation. However, it is not necessary reasonable to have a correlation of zero, even if it is considered computationally simpler (Lindell-Murray-Tuite et al. 2019). Here uncertainty about departure distributions becomes an issue to be addressed; mainly by examining the variations in departure curves that were reported for a variety of different hazards (Lindell, Murray-Tuite et al. 2019). Data from Rogers and Sorensen's (1989) study of hazardous materials incidents in Confluence and Pittsburg Pennsylvania provide good examples of variation in departure time distributions across incidents. The Confluence incident generated a rapid warning distribution and almost everyone evacuated soon after receiving a warning. Contrasting is the Pittsburgh incident that generated a somewhat slower warning distribution and only about half of those who received a warning evacuated and those who did evacuate took much longer to do so.

A few studies developed explanatory models of evacuation timing decisions. Variables such as environmental, social and demographic factors, risk perception, household location, destination characteristics, socio-economic characteristics, and evacuation notice were key determinants of the departure time (Lindell and Prater, 2007; Hasan et al., 2013). Most hurricanes have days of tracking and evacuation notices are issued many days in advance, which leads to having evacuation departures distributed over multiple days (Huang et al. 2016). For example, in Hurricane Ike, about 15% of people evacuated before the National Hurricane Center (NHC)

Hurricane Watch. Another 20% evacuated in the next 18 hours before the NHC Hurricane Warning, and the remainder evacuated afterwards (Lindell, Murray-Tuite et al. 2019). Over time, it has been noticed that there are consistent spikes of evacuation departures during the late morning and afternoon followed by a substantial decline in the evening (Lindell, Murray-Tuite et al. 2019); this is due to peoples' preference to evacuate during the day and avoid departing during night time but will do so if they have to (Lindell, Murray-Tuite et al. 2019). Examples of hurricane nighttime evacuations are Eloise (Baker et al. 1976), Opal (USACE Philadelphia District 1996) in Florida, and Elena (Baker 1986).

2.5 Gaps in Previous Studies

Previous literature , in terms of the evacuation decision, has studied a wide variety of variables that have an effect on the binary evacuate/stay decision of households. On the other hand, partial household evacuation has received less attention than the binary evacuate/stay decision. This study account for three outcomes for a household's evacuation decision, instead of only two, which allows capturing new variables that reflect complexity of decision-making at the household level.

Other evacuation aspects such as the number of evacuating vehicles and evacuation departure timing were studied previously. However, these provided a range of the number of evacuating vehicles per household rather than an accurate number, which produces a huge difference in the number of vehicles when taking into account the total number of evacuating households. This makes it necessary to provide better prediction of the total number of evacuating vehicles; this dissertation addresses this gap in the literature and provides better understanding of the factors affecting household choice of the number of household vehicles used in evacuation, thus a better prediction of the number of evacuating vehicles; and eventually a better overall evacuation vehicle demand estimation. This study also introduced a new number of factors to be considered in this context, including uncertainty, partial household evacuation, and family cohesion. Zero truncated Poisson regression was utilized in this study, making it the first study of the number of evacuating vehicles to use this method.

Finally, previous literature studied the departure timing choice of households by providing empirical models of departure timing. However, a small number of studies provided behavioral models of departure timing compared to the empirical studies. This dissertation is among those who studied the affecting factors of evacuation departure timing and included newly introduced factors that were significant on the evacuation departure timing, which will allow a better prediction of the dynamic evacuation demand.

2.6 References

Baker, E.J., 1991. Hurricane evacuation behavior. International journal of mass emergencies and disasters, 9(2), pp.287-310..

Baker, E.J., 2000. Hurricane evacuation in the United States. Storms, 1, pp.306-319.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica (pre-1986), 39(5), p.829.

Dow, K. and Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natural hazards review, 3(1), pp.12-18.

Greene, W.H., 1998. *Limdep*.

Hunt, M.G., Bogue, K. and Rohrbaugh, N., 2012. Pet ownership and evacuation prior to Hurricane Irene. Animals, 2(4), pp.529-539.

Lindell, M.K., Kang, J.E. and Prater, C.S., 2011. The logistics of household hurricane evacuation. Natural hazards, 58(3), pp.1093-1109.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. and Baker, E.J., 2019. Large-scale evacuation. New York: Routledge.

Maghelal, P., Peacock, W.G. and Li, X., 2016. Evacuating together or separately: factors influencing split evacuations prior to Hurricane Rita. Natural Hazards Review, 18(2), p.04016008.

Martín, Y., Li, Z. and Cutter, S.L., 2017. Leveraging Twitter to gauge evacuation compliance: Spatiotemporal analysis of Hurricane Matthew. PLoS one, 12(7), p.e0181701.

"National Oceanic and Atmospheric Administration (NOAA). (2011).

National weather service weather fatality, injury and damage statistics, ⟨http://www.weather.gov/om/hazstats.shtml⟩ (Jul. 7, 2012)."

McFadden, D., 1977. Quantitative methods for analyzing travel behavior of individuals: some recent developments. Berkeley: Institute of Transportation Studies, University of California.

Perry, R.W., Lindell, M.K. and Greene, M.R., 1981. Evacuation planning in emergency management

Thompson, R.R., Garfin, D.R. and Silver, R.C., 2017. Evacuation from natural disasters: a systematic review of the literature. Risk analysis, 37(4), pp.812-839.

Van Der Heijden, P.G., Cruyff, M. and Van Houwelingen, H.C., 2003. Estimating the size of a criminal population from police records using the truncated Poisson regression model. Statistica Neerlandica, 57(3), pp.289-304.

Wu, H.C., Lindell, M.K. and Prater, C.S., 2012. Logistics of hurricane evacuation in Hurricanes Katrina and Rita. Transportation research part F: traffic psychology and behaviour, 15(4), pp.445-461.

Wu, H.C., Lindell, M.K., Prater, C.S. and Huang, S.K., 2013. Logistics of hurricane evacuation in Hurricane Ike. Logistics: perspectives, approaches and challenges. Nova Science, Hauppauge, pp.127-140.

Yin, W., Murray-Tuite, P. and Gladwin, H., 2014. Statistical analysis of the number of household vehicles used for Hurricane Ivan evacuation. Journal of Transportation Engineering, 140(12), p.04014060.

Yin, W., Murray-Tuite, P.M., Ukkusuri, S.V., Galdwin, H. 2014c. Pre-evacuation activities for hurricane evacuation: an analysis of behavioral intentions from Miami Beach, Florida. 93rd Annual Meeting of the Transportation Research Board, Washington, DC.

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A. and Smith, G.M., 2009. Zero-truncated and zero-inflated models for count data. In Mixed effects models and extensions in ecology with R (pp. 261-293). Springer, New York, NY.

CHAPTER THREE

MODELING FULL AND PARTIAL HOUSEHOLD EVACUATION FROM HURRICANE MATTHEW WITH A MIXED MULTINOMIAL LOGIT MODEL

Roaa Alawadi[a] , Pamela Murray-Tuite[b], David Marasco[c], Satish Ukkusuri[d], Yue Ge[e]

[a] Research Assistant, Glenn Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 864-643-8778; Email: ralawad@clemson.edu

[b] Associate Professor, Glenn Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 864-656-3802; Email: pmmurra@clemson.edu

[c] Research Assistant, Glenn Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 864-643-8778; Email: dmarasc@clemson.edu

[d] Professor, Lyles School of Civil Engineering, Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907; Tel: (765) 494-2296; Email: sukkusur@purdue.edu
[e] Assistant Professor, School of Public Administration, University of Central Florida, 12494 University Blvd., Orlando, FL 32816; Tel: 407-823-4376; Email: yue.ge@ucf.edu

Dr. Pamela Murray-Tuite revised the overall paper content as well as her guidance in the model choice, hypotheses adopted, and literature review. David Marasco contributed in the weighting process of the data. Both Dr. Ukkusuri and Dr. Ge reviewed the overall paper content and provided their input of previous literature.

3.1 Abstract

Hurricane evacuation decision is considered a complex process that includes different influencing factors. This paper takes a step further in studying evacuation decision by presenting three level evacuation decision models that includes Full, partial, and no evacuation alternatives. Multinomial (MNL) regression and Random parameter MNL were utilized to develop the prediction models. Results showed that some of the variables which affect the evacuate/stay decision have different influence on the three level study of evacuation. These finding are significantly important to better help understand the complexity of decision making in households.

Keywords: Hurricane evacuation; Partial Household evacuation; Random parameters; Hurricane Matthew

3.2 Introduction and Background

Hurricane evacuation research is becoming increasingly important, due to the continuous population growth on both the Atlantic and Gulf coasts, the inability of the transportation infrastructure to keep up with this growth (Dow & Cutter 2002), and the high cost associated with these hazards (National Hurricane Center (NHC) 2006). With the rise in population and the infrastructure constraints, evacuation demand models would benefit from greater resolution, such as considering full, partial, and no household evacuation. The ability to predict the characteristics and number of evacuees facilitates managing the evacuation process, which can help reduce the potential for being trapped on highways during the hurricane and associated deaths due to storm surge (Lindell et al. 2005).

Over the past several decades, considerable research studies focused on factors affecting the hurricane evacuate/stay decision of residents (C. Gladwin, Gladwin & Peacock 2001). Such factors include household socio-economic and demographic factors (age, gender, ethnicity, education, etc.). However there are mixed findings on socio-economic and demographic factors; Lindell et al. (2019) argued that these factors do not predict evacuation behavior as well as other factors such as risk area, hearing evacuation notices, housing type and perceived vulnerability. Huang et al. (2016b) agreed with Baker (1991) that demographic variables are weak and inconsistent predictors of evacuation. Other factors affecting the hurricane evacuate/stay decision include hurricane characteristics (path, intensity, etc.) and emergency management practices (mandatory or voluntarily evacuation notice) (Solis, Thomas, & Letson, 2010).

This paper contributes to hurricane evacuation research by accounting for partial household evacuation and using random parameters in the prediction models, which allow mixed parameter effects. Accounting for partial household evacuation helps to better understand complex human behavior, identify potentially nuanced variable effects, and could lead to better evacuation predictions. Random parameters multinomial logit (MNL) models are used to account for three alternatives of full, partial, and no household evacuation and the heterogeneity of parameters across households in a sample of Jacksonville, Florida residents' responses to Hurricane Matthew. New variables, such as certainty about hurricane characteristics, are also considered in this study. Additional factors investigated include information on the household socioeconomic and demographic characteristics, home ownership and residence type, and past hurricane experience.

The remainder of this paper is organized into six sections. The first presents a selection of related literature and hypotheses investigated in this study. The second and third sections discuss the data and modeling methodology. The fourth section presents results of the study, followed by a discussion of the findings. The final portion provides conclusions and suggestions for future research.

3.3 Literature Review and Hypotheses

Quarantelli (1980) showed that the characteristics of the received warning messages including credibility, frequency, and specificity were significant factors affecting the decision to evacuate or not. Baker (1991) added that how residents obtained risk information was a major factor affecting the evacuation decision. Warning response varies with warning source, content, the number of warnings received and the belief of the warning itself (Mileti et al. 1975). Responses to warnings are also influenced by the sender and receiver characteristics (Sorenson & Vogt-Sorenson 2006). However, Dow & Cutter (1998) suggest that the household evacuation decision is affected more by media and household characteristics than the actual warning.

Baker (1991) emphasized the false experience problem as an indicator of evacuation, it occurs when people were not exposed to real threat of the hurricane (e.g., hurricane missed them) and their houses withstood against wind and storm surge. The effect of false alarms on future evacuations, is referred to as the "crying wolf syndrome" (Breznitz, 1984). However, the literature has mixed findings about unnecessary evacuations; Lindell et al. (2019) stated that there is little evidence of the negative effect of false experience, pointing to when people were asked about the reason why they did not evacuate, few say that it is because they evacuated unnecessarily in the past. In 1985, the residents of Panama City Beach, Florida were asked to evacuate three times in the same hurricane season. The evacuation rates were essentially the same even though the storms missed their community all the three times (Baker 1991).

A wide range of variables that affect the evacuation behavior were studied throughout the literature. Some were found to be strong predictors of evacuation such as risk areas, housing type, hearing evacuation notices, and perceived vulnerability (Lindell et al. 2019). However other factors such as socio-economic and demographic variables do not predict evacuation as well as the factors listed above (Lindell et al. 2019).). Previous models of evacuation behavior did not account for the heterogeneity that exists from individuals to individuals due to differences in the production of risk perceptions. Based on this, Hasan et al. (2011) developed a household-level mixed logit model of hurricane evacuation decision where random parameters account for the heterogeneous responses of households to a major hurricane using original data from Hurricane Ivan (Hasan, Ukkusuri et al. 2010). The study reported factors important for understanding evacuation decision behavior and revealed heterogeneities in terms of location, evacuation notice, work constraint, and the number of children. Previous hurricane experience may seem a strong predictor of evacuation, but recent studies by Huang, Lindell and Prater (2016b) found no consistent relationship between experience and evacuation. Literature also has somehow mixed results of other factors such as information sources. For example, a study by Dow and Cutter (2000, 2002) showed that coastal residents have many risk information sources other than the information issued by official sources. Thompson, Garfin, and Silver (2017) showed that law enforcement officers have the greatest credibility and that news and peers are important warning sources. Additional factors are listed in Table 3-1 along with their direction of effect on the likelihood of evacuating.

Table 3-1.Factors affecting evacuation decision.

Factor	Effect on evacuate decision	Sources
Socio-economic and demographic factors		
Age (older)	-	(Lindell, et al., 2005; Thompson et al. 2017)
Gender (Female)	+	Fothergill 1996; Riad, Norris and Ruback 1999; Whitehead et al. 2000; cc; Bateman & Edwards 2002; Lindell et al. 2005; Thompson et al. (2017)
Income	+	H. Gladwin & Peacock, 1997; Elliott & Pais, 2006; Hasan, et al., 2011)
Race (African American)	-	Gladwin & Peacock (1997)
Race (white)	+	Thompson et al. (2017)
Marital status (Single people)	+	Wilmot and Mei (2004)
Past hurricane experience		
Previously evacuated	+	(Riad, et al. (1999)
Previous experience	-	Baker 1991
Household structure		
Presence of elders	-	(Gladwin & Peacock (1997); Dash & Gladwin (2007); Thompson et al. (2017)
Presence of Children	-	Thompson et al. (2017)
Pet ownership	-	Thompson et al. (2017)
Greater a family's cohesion	+	Perry (1979)
Storm characteristics		
Intensity	+	Whitehead (2000)
Housing type and duration of residence		

Living in mobile homes	+	(Baker, 1991; Whitehead, 2000; Wilmot & Mei, 2004; Solis, et al., 2010; Hasan, et al., 2011; Huang, Lindell, and Peter, 2016b)
Living in single family dwellings	-	Wilmot & Mei (2004)
Duration of residence (longer)	-	(H. Gladwin & Peacock, 1997)
Geographic location		
Proximity to water	+	Wilmot & Mei (2004)
Evacuation notice		
Receipt of an official evacuation order	+	(Wilmot & Mei (2004); Huang, Lindell, and Peter, 2016b)
Receiving a mandatory evacuation notice	+	(Baker 1991; Whitehead et al. 2000)

3.4 Partial Household Evacuation

Partial household evacuation has received less attention than the binary evacuate/stay decision. Lim et al. (2015) studied household evacuation and included partial household evacuation in a study after a flood hit Quezon City, Philippines. They developed a multinomial logit model (MNL), the results of which show that the evacuation decision is dependent upon a combination of household characteristics and capacity related factors (gender, educational level, presence of children, and number of years living in the residence, house ownership, number of house floor levels, type of house material), as well as hazard related factors (distance from source of flood, level of flood damage, and source of warning). Another study by Stopher et al. (2004) studied three decision levels of household evacuation, full, partial, and no evacuation in the context of bushfire. They developed multinomial (MNL) and mixed logit (ML) models, and found that a number of household socio-demographic characteristics and decision maker characteristics were significant predictors of the three level evacuation decision and continued to find the percentages of each level of evacuation by simulation processes. Accounting for three outcomes for a household's evacuation decision, instead of only two, could allow capturing new variables or nuances in variable effects that reflect complexity of decision-making at the household level.

3.5 Prior Findings on Mixed-Effects

Previous work also addresses the issue of variable effects (heterogeneity) of the attributes on certain evacuation decisions using random parameter models (Hasan et al, 2011; Mesa Arango et al, 2012). For the evacuation decision, a logit outcome model of hurricane evacuation decision using the random-parameters modeling technique of econometrics (known as mixed logit or random-parameters logit) where the random-parameters associated with different variables reflect the heterogeneity of households' responses due to a hurricane threat. In the study (Hasan et al, 2011), it was found that the location of household (either in Florida or Louisiana) had mixed effects. For example, the parameter for the indicator variable for the households from Florida is found as random with mean 1.522 and standard deviation 1.75 implying that for 19 percent of the households, being from Florida results in a higher probability to evacuate, while for 81 percent of households, being from Florida results in lower probability to evacuate. Variables related to household having children under 18 and if the household member had to work during the evacuation also have mixed effects from the model. Similar mixed effects are also found in the choice of the evacuation destination (Mesa Arango et al 2012). The mixed effects explain clearly the variability of the effects across different households which should be considered during policy making.

3.6 Hypotheses

Commonly discussed hypotheses in the literature were adopted for initial selection of the investigated variables of this study. These hypotheses are already explored in the literature for the evacuate/stay evacuation decision. However, they were not studied in the context of three level evacuation decision (none, partial, and full evacuation). Further investigation of these hypotheses is needed in order to better understand the complexity of the hurricane evacuation decision. The adopted hypotheses are summarized as follows:

- H1: Greater family cohesion is negatively associated with partial household evacuation.

Perry (1979) suggested that more cohesive families are more likely to evacuate. Savitt and Ge (2018) reviewed the family science literature about characteristics and quality of family relations and interactions that affect intra-family decision making in disaster evacuations, where cohesion of the family is identified as one of the intangible resources that contribute to stress management and decision making within families. We anticipate that better relationships among household members would make evacuation decision making outcomes more uniform within the household so that they decide to either evacuate or stay together, which may lead to less chance of a partial household evacuation.

- H2: Living in a mobile home is positively related to both partial and full household evacuation.

Wilmot and Mei (2004) studied the evacuation decision of Louisiana residents from Hurricane Andrew, their results showed that mobile home residents are more likely to evacuate. Other studies by Baker (1991), Whitehead (2000), Wilmot and Mei (2004), Solis, et al. (2010), Hasan, et al. (2011), and Huang, Lindell, and Prater (2016b) found the same effect of living in mobile homes on the evacuation decision. These findings come from the fact that mobile homes are more vulnerable against hurricanes, which may lead to more partial and full household evacuation among residents of mobile homes.

- H3: Living in a single family dwelling is negatively related to evacuation.

Wilmot and Mei (2004) found that residents of single family dwelling homes are less likely to evacuate. These assumptions could be explained due to the fact that single family homes are structurally more resistant to wind surge than other mobile or manufactured homes, thus households may feel safe enough not to leave. Single family homes are also more likely to be owned by the residents compared to multifamily dwellings, such as apartments. Thus, single family home residents may be more likely to stay to try to protect their property. However, evacuation decision disagreement may arise among residents of single family homes which could lead to more partial and less full household evacuation.

- H4: Marital status (married) is negatively related to evacuation.

Wilmot and Mei (2004) stated that single, divorced, and separated people are more likely to evacuate than those who are married. These findings could be explained by the decision making process being easier for single people than married couples as there is less chance of conflicting perspectives among adults in the household. Such households may also have fewer resources within the household (i.e., adults) with which to cope with damaging effects, encouraging them to evacuate. However, if married couples evacuate, they are expected to be more likely to evacuate together, which could lead to more full household evacuation and less partial household evacuation.

- H5: Risk perception is positively related to both partial and full household evacuation.

Perry (1979) concluded that the evacuation decision is correlated to people's prior perception of risk. Mileti et al. (1975) argued that if people do not believe the reality of the risk then they are less likely to evacuate, and when households feel their lives or those of their loved ones are in danger, they are more likely to evacuate. Other studies by Baker (1991), Gladwin &Peacock (1999), Whitehead, et al. (2000), Dow and Cutter (2000), Fu and Wilmot (2004), among many others, found higher risk perception is positively related to evacuation. These studies imply that higher risk perception could lead to more partial and entire household evacuation.

- H6: Respondent age (older) is negatively related to partial household evacuation.

Lindell, et al. (2005) and Thompson, et al. (2017) found that older people are less likely to evacuate. This could be explained by mobility issues, lack of resources, or discomfort with stressful driving conditions. We anticipate that older respondents would be more likely to have the same behavior as the rest of their household for comfort and shared resources.

- H7: Greater certainty about hurricane characteristics is positively related to both partial and full household evacuation.

Quarantelli (1980) argued that the characteristics of the received messages including credibility of the warning message affects the evacuation decision. When people receive more credible messages about hurricane characteristics, this leads to increasing their certainty, which could lead to greater likelihood of partial and full household evacuation.

3.7 Data

The sample used consists of 588 respondents of a household mail survey conducted in the wake of the 2016 Hurricane Matthew in the 1.3 million population metropolitan area of Jacksonville, Florida. During the summer and fall in 2017, four waves of mailings (i.e., three complete survey packets and a postcard reminder) were implemented using the standard procedure recommended by Dillman, Smyth, and Christian (2014). In each wave, the survey questionnaire was assembled into four different versions where the four major blocks of questions (i.e., uncertainty factors and evacuation behaviors, social network information, intra-family decision making factors, and information sources) were placed in different sequences with household demographic questions at the end to avoid potential low response rates for questions at the latter part of the survey.

Data collected included household socio-demographic information, housing type and location, house ownership status, past hurricane experience, evacuating or not evacuating, whether a hurricane evacuation notice was received, type of the notice received (mandatory or voluntary), media thorough which the evacuation notice was received (i.e., TV/Radio, Friends, Relatives, etc.), the time of evacuation if evacuation occurred. (Survey information to be added).

Because the data sample is biased towards certain demographics relative to the population (including gender, age group, education level, marital status, and income; (see Table 3-2), the researchers needed a method to weight the observations. Weighting allows the responses of underrepresented groups to have increased impacts on the model outcome, thereby better reflecting the tendencies of the actual population. Rake weighting (or "raking") is an expedient method for applying weights based on comparisons of demographic distributions in a data sample and an overall population (Pew Research 2018). In this study, the rake weighting was based on three demographic variables: gender (male or female), education level (four-year college degree or lack thereof), and age group (18 through 44, 45 through 59, and 60+). These variables are not correlated, which is a requirement of the raking process.

Table 3-2. Demographic distributions of the data sample and the 2016 population of Jacksonville, FL (ACS 2018).

Attribute	Category	Population	Sample	Bias	Average bias
Age group	**18 to 44**	0.50	0.18	0.32	0.21
	45 to 59	0.26	0.31	0.05	
	60 or over	0.24	0.51	0.27	
Education level	**no four-year college degree**	0.73	0.33	0.4	0.4

	four-year college degree	0.27	0.67	0.4	
Gender	**female**	0.52	0.59	0.07	0.07
	male	0.48	0.41	0.07	
Income (annual)	**less than $15,000**	0.12	0.04	0.08	0.06
	$15,000 to $30,000	0.15	0.09	0.06	
	$30,000 to $45,000	0.16	0.11	0.05	
	$45,000 to $60,000	0.14	0.14	0	
	$60,000 to $100,000	0.24	0.28	0.04	
	over $100,000	0.19	0.34	0.15	
Marital status	**not married**	0.54	0.26	0.28	0.28
	married	0.46	0.74	0.28	

The two demographic variables that were not used to weight the sample were instead used to test whether or not the raking reduced the bias outside of the raking variables themselves (Table 3-3) (Pew Research 2018).

Table 3-3. Evaluation of bias before and after rake weighting based on marital status and income

Marital status	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
Not married	0.54	0.26	0.28	0.35	0.19	-0.09
married	0.46	0.74	0.28	0.65	0.19	-0.09
Average			0.28		0.19	-0.09
Income level	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
1	0.12	0.04	0.08	0.08	0.04	-0.04
2	0.15	0.09	0.06	0.15	0.00	-0.06
3	0.16	0.11	0.05	0.14	0.02	-0.03
4	0.14	0.14	0.00	0.14	0.00	0.00

5	0.24	0.28	0.04	0.26	0.02	-0.02
6	0.19	0.34	0.15	0.23	0.04	-0.11
Average			0.06		0.02	-0.43
	Initial bias	**Weighted bias**	**Bias change**			
Overall	0.17	0.11	-0.06			

The calculations show that the sample bias was reduced to (11%) a decrease of (6%). This demonstrates that the rake weighting had a distribution improvement effect on the sample beyond the three variables that were included in the raking process, as was intended.

Table 3-4 presents summary statistics of the explanatory variables selected for the model.

Table 3-4. Summary statistics of the selected explanatory variables.

Variable	Minimum	Maximum	Mean	Standard deviation
Living in single family detached homes (0: no; 1: yes)	0	1	0.88	0.32
Living in mobile homes (0: no; 1: yes)	0	1	0.03	0.17
Married (0: no; 1: yes)	0	1	0.72	0.45
Injury concern (Risk perception) (1-5; 1: smallest, 5: highest)	1	5	2.22	1.25
Family cohesion level (1-5; 1: low, 5: High)	1	5	4.50	0.81
Respondent Age (20 to 92 years)	20	92	57.97	14.13
Certainty about hurricane impact location (1: not certain, 5: Extremely certain)	1	5	3.75	1.10
Previously evacuated (0: no; 1: yes)	0	1	0.28	0.45

Certainty about whether they live in an evacuation zone (1: not certain, 5: Extremely certain)	1	5	4.37	1.15
Gender (0: Female; 1: Male)	0	1	0.41	0.49
Number of household members under 18 years	0	6	0.69	1.08
Number of household members between 18 and 65 years	0	6	1.65	0.98
Number of household members with medical conditions	0	1	0.18	0.38
Number of years in current home	0	63	14.13	12.24
Number of years in current community	0	74	19.20	16.28
Distance to coast (miles)	0	56	10.46	12.62
Race black (0: No; 1: Yes)	0	1	0.01	0.08
Race white (0: No; 1: Yes)	0	1	0.9	0.30

3.8 Methodology

In this study, the household evacuation decision has three possible outcomes; none, partial, and full household evacuation. The MNL model can be appropriate for this kind of discrete outcome; however, the assumption made in the application of the MNL is that parameters are fixed across all observations. If this assumption does not hold, inconsistent estimation of parameters will result (Washington et al. 2011). In this case, random parameters (mixed logit) are considered to account for the heterogenous effects across observations.

At the heart of logit-based models is the utility expression, represented by equation (1) as presented by Train (2003) and described in Washington et al. (2011).

$$T_{in} = \beta_i X_{in} + \varepsilon_{in} \qquad \text{Eq. 3-1}$$

where

T_in = the utility of alternative i for household n;

β_i = vector of estimable parameters for the discrete outcome i;

X_in= vector of the factors (covariates) that influence the evacuation decision outcome for household n; and

ε_in = disturbance term.

If the disturbances ε_in are assumed as extreme-value Type I distributed, then the MNL form for the evacuation decision outcome follows equation (3-2) (Train 2003; Washington et al. 2011):

$$P_n(i)=\frac{e^{\beta_i X_{in}}}{\sum e^{\beta_j X_{jn}}} \qquad \text{Eq. 3-2}$$

where

P_n(i) = the probability of household n selecting alternative i and other notation is as previously described.

To allow for parameter variations across households (represented by variations in β), Eq. 3-3 defines a mixed model (Train 2003; Washington et al. 2011):

$$P_n^m(i) = \int P_n(i)\, f(\beta|\varphi) d\,\beta \qquad \text{Eq. 3-3}$$

where

$f(\beta|$φ)= the density function of β, with φ referring to a vector of parameters of that density function (e.g., mean and variance).

Substituting Eq.(3-2) into Eq.(3-3) gives the mixed logit model probabilities as shown in equation (4). In the simplified case when $f(\beta|\varphi)$=1, the model reduces to the standard MNL. Some of the parameters β may be fixed and some may be random (Train 2003; Washington et al. 2011).

$$P_n^m(i) = \int \frac{e^{\beta_i X_{in}}}{\sum e^{\beta_i X_{In}}} f(\beta|\varphi) d\,\beta \qquad \text{Eq.3-4}$$

Where

$P_n^m(i)$ = the weighted average of the standard MNL probabilities P_n (i), with the weights determined by the density function $f(\beta|\varphi)$.

Estimation of the mixed logit model in Eq.(3-4) by maximum likelihood is determined using simulation approaches because of the difficulties in computing the probabilities. Gkritza and Mannering (2008) argued that numerical integration of this function would make the estimation method computationally difficult. The mixed logit probabilities $P_n^m(i)$ are first approximated by drawing values of β from $f(\beta|\varphi$ given the values of φ, which are used to estimate a simple logit probability (Eq.(3-2)). This procedure is repeated using many draws, and the computed logit probabilities are summed and averaged to obtain the simulated probability $\hat{P}_n^m$, which is used to compute a likelihood function that is finally maximized to estimate the parameter vectors β and φ. For drawing values of β from $f(\beta|\varphi)$,random draws and Halton draws are usualy considered to obtain accurate approximations of the probabilities with as few draws as possible. Train (2003) reviewed a wide variety of sampling techniques that are often used in this context. However, the most popular is Halton draws; this technique was developed by Halton (1960) to generate a random sequence of numbers. Halton draws has been shown to be more efficient than purely random draws (Bhat 2003).

The selection of initial variables was based on previous evacuation literature and the previously stated hypotheses. A MNL model was developed based on a number of trials where all the variables in Table 2 were examined and non-significant variables were removed one by one in a backward step-wise fashion. Variables were considered significant if their p-value was 0.1 or less. Correlation was tested between variables, and no factors with correlation of 0.3 or more were considered in the same model (see Appendix). The selected MNL model was then tested for random parameters. Then a likelihood test was used to determine whether the mixed logit model is preferred to the fixed parameter model. The likelihood ratio (LR) can be calculated as in equation (3-5) (Washington et al., 2011):

$$LR = -2[LL(\beta_{Fixed}) - LL(\beta_{Random})] \qquad \text{Eq. 3-5}$$

where

$LL(\beta_{Fixed})$= the log-likelihood at convergence for the fixed parameters model and

$LL(\beta_{Random})$ = the log-likelihood at convergence for the random parameters model.

The LR is $\chi 2$ distributed and has degrees of freedom equal to the number of estimated random parameters. The McFadden's Pseudo R-Squared value computed in equation (6) can be used to assess the random parameters model when it is preferred over the fixed parameters model.

$$\text{Pseudo}^2 = 1 - \frac{LL(\beta_{\text{Random}})}{LL(0)} \qquad \text{Eq. 3-6}$$

where LL(0) is the log-likelihood at zero (McFadden, 1981; McFadden and Train, 2000).

3.9 Results

The preferred MNL model was tested for random parameters and one random parameter (age of the respondent) was identified for the utility expression pertaining to the no evacuation alternative (Table 3-5). In the estimated model $LL(\beta_{Fixed})$ is -1941.463 and $LL(\beta_{Random})$ is -1931.266, this results in LR of 20.394 and one degree of freedom. These values, combined with equation (3-5), indicate that with more than 99% significance, the random parameters model is preferred. Equation (3-6) with $LL(\beta_{Random})$ of -1931.266 and LL(0) -2649.356 yields the Pseudo

R-Squared value of 0.271, which represents an excellent fit of the current model specification (McFadden 1977).

3.9.1 None of The Household Evacuates

For the utility expression for this alternative, five factors are statistically significant. Age of the respondent has heterogenous effects on the evacuation decision with normal distribution based on the statistical significance of the standard deviation. Age has an estimated parameter coefficient of .082 and standard deviation of .077. Based on the normal distribution, these values indicate that the effect of older age is negative for 14.460% of the respondents, which means that they are less likely to have none of their household evacuate. For this 14.460%, the households are more likely to either partially or fully evacuate. However, for the other 85.540%, the effect of age is non-negative and increased age increases the likelihood that the household stays.

According to marginal effects in Table 3-6, three variables have negative effects on the probability of the entire household staying. First is injury concern; a unit increase in injury concern decreases the likelihood of none of the household evacuating by -0.317. Second is living in a single family detached home; where living in detached homes decreases the likelihood that none of the household evacuates by -0.119. Third is living in mobile homes; this means that living in mobile homes decreases the likelihood that none of the household evacuates by -0.014. One variable had a positive effect; being married increases the likelihood that none of the household evacuates by 0.226.

3.9.2 Partial Household Evacuation Decision

In the mixed logit model, partial household evacuation decision was considered as the base case. According to the marginal effects (Table 3-6), an increase in family cohesion decreases the likelihood of partial evacuation by -0.257. Age and married also have negative effects on partial household evacuation. An addition year of age decreases the likelihood of partial household evacuation by -0.119, and being married decreases the likelihood of partial evacuation by -0.057.

The remaining four variables have positive effects. An increase of injury concern increases the likelihood of partial household evacuation 0.079. Living in a single family detached home increases the likelihood of partial household evacuation by 0.027. Living in a mobile home increases the likelihood of partial household evacuation by 0.029. Finally, an increase in hurricane impact location certainty increases the likelihood of partial household evacuation by 0.055.

3.9.3 Full Household Evacuation

For the full household evacuation alternative, seven factors are statistically significant. According to the marginal effects (Table 3-6), three of these factors have positive effects on the full household evacuation alternative. Being married increases the likelihood of full household evacuation by 0.149. An increase in the self-reported family cohesion score increases the likelihood of full household evacuation by 0.573. An additional year of age increases the likelihood of full household evacuation by 0.282.

The remaining four variables have negative effects. First is injury concern, where greater injury concern decreases the likelihood of full household evacuation by -0.133. Second and third are living in detached and mobile homes, where living in detached home decreases the likelihood of full household evacuation by -0.300, and living in a mobile home also decreases the likelihood of full household evacuation by -0.340. Finally, more certainty about the hurricane impact location decreases the likelihood of full household evacuation by -0.120.

Table 3-5. Final fixed parameter and random parameter model of household evacuation decision

Variable description	Fixed Parameters model						Random parameters model					
	No household evacuation		Partial household evacuation		Entire household evacuation		No household evacuation		Partial household evacuation		Entire household evacuation	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient (SD)	Standard error	Coefficient	Standard error	Coefficient	Standard error
Fixed Parameters							**Fixed Parameters**					
Constant	-	-	-2.068**	0.546	-2.209***	.408	-	-	-1.541***	0.771	-3.703***	0.805
Injury concern	-1.057***	0.061	-	-	-0.419***	.055	-1.941***	0.040	-	-	-0.478***	0.061
Living in detached home	-2.472***	0.476	-	-	-3.282***	0.460	-1.702***	0.630	-	-	-3.083***	0.459
Living in mobile home	-5.168***	0.555	-	-	-4.139***	0.504	-8.079***	1.604	-	-	-3.780***	0.501
Married	2.159***	0.181	-	-	1.833***	0.180	3.251***	0.594	-	-	1.577***	0.202
Family cohesion	-		-	-	0.549***	0.069	-	-	-	-	1.071***	0.146
Age	0.059	0.006	-	-	0.058***	.006	-	-	-	-	0.056***	.007
Hurricane Impact location certainty	-	-	-	-	-0.257***	0.041	-	-	-	-	-0.282***	0.068
							Random parameters					
Age							0.082***	0.014				

Model Statistics

Number of Observations	360
Log-Likelihood at Zero	-2649.356
Log-Likelihood at Convergence (fixed)	-1941.463
Log-Likelihood at Convergence (random)	-1931.266
McFadden Pseudo R-Squared	0.271

Note: ***, **, * ⟹ Significance at 1%, 5%, 10%

Table 3-6. Marginal effects for household evacuation decision.

Variable description	No household evacuation	Partial household evacuation	Entire household evacuation
Injury concern	-0.317	0.079	-0.133
Living in detached home	-0.119	0.027	-0.300
Living in mobile home	-0.014	0.029	-0.340
Married	0.226	-0.057	0.149
Family cohesion	n.s.	-0.257	0.573
Age	0.274	-0.119	0.282
Hurricane impact location certainty	n.s.	0.055	-0.120

3.10 Discussion

This section discusses the results in terms of the hypotheses.

- *H1: Greater family cohesion is negatively associated with partial household evacuation.*

This hypothesis was supported. In our model, greater family cohesion was associated with the household remaining together, particularly evacuating as a whole, consistent with Perry (1979).

- *H2: Living in a mobile home is positively related to both partial and full household evacuation.*

This hypothesis was supported with respect to partial household evacuation but rejected for full household evacuation, partially deviating from prior literature. Living in mobile homes decreases the likelihood that none of the household evacuates (consistent with prior literature), and increases partial household evacuation, but decreases the likelihood of full household evacuation. This result, partially differing from prior literature (Baker (1991), Whitehead (2000), Wilmot & Mei (2004), Solis, et al. (2010), Hasan, et al. (2011), and Huang, Lindell, and Prater (2016b)), suggests that the effect of this variable could be more nuanced. Potentially, there may be disagreement among residents of mobile homes about the evacuation decision, which may lead to more partial evacuation and less full household evacuation. Resource-constrained households living in mobile homes may also face trade-offs between the risk of injury to household members from the hurricane and the desire to protect their property. Finally, the households' decision-makers may send vulnerable members with other relatives or trusted neighbors while those who remain behind try to protect their property.

- *H3: Living in a single family dwelling is negatively related to evacuation.*

The support for this hypothesis is mixed. In this model, living in a single family detached home leads to less likelihood of none of the household evacuating, more likelihood of a partial household evacuation, and less likelihood of full evacuation. Potentially, some of the household members feel safe enough in well-constructed single family dwellings to remain behind, but still have more vulnerable household members (e.g., children) evacuate to provide additional protection for them and because caring for them in a damaged or disrupted community after the hurricane could be challenging.

- *H4: Marital status (married) is negatively related to evacuation.*

In the proposed model "married" marital status was tested and the results show that married households have a higher likelihood of none of the household evacuating and less partial and more entire household evacuation likelihood. These results partially support the stated hypothesis. A married couple is more likely to be united in their decision to stay or evacuate as a whole and less likely to partially evacuate.

- *H5: Risk perception is positively related to both partial and full household evacuation.*

In the proposed model, risk perception effect was tested by introducing (Injury concern) variable. Support for this hypothesis was mixed. The results show that more injury concern results in less likelihood of none of the household evacuating, greater likelihood of partial household evacuation, and less likelihood of full household evacuation. This could be explained by disagreement among household members about the risk and evacuation decision, which decreases the percentage of full household evacuation.

- *H6: Respondent age (older) is negatively related to partial household evacuation*

This study's results support the hypothesis. Older respondents are less likely to have split decision households and more likely to either all stay or all evacuate.

- *H7: Greater certainty about hurricane characteristics is positively related to both partial and full household evacuation.*

Using impact location as the hurricane characteristic, this hypothesis was supported with respect to partial household evacuation but rejected for full household evacuation. Greater certainty may have imparted greater confidence that the hurricane would not directly impact them, prompting evacuation of vulnerable household members but giving some household members confidence in remaining behind.

3.11 Conclusions

This paper investigates the evacuate stay decision based on three alternatives (no, partial, and full household evacuation). This study is among the few that have studied the partial household evacuation, using multinomial logit models with and without random parameters, the latter of which are used to account for the heterogeneity of the parameter effects. The random parameter model (with age as the only random parameter) was preferred to the fixed parameters model. The other variables significant in this model were injury concern, certainty about hurricane impact location, age, marital status, family cohesion, and living in mobile or detached home.

The inclusion of partial household evacuation suggests that the effects of several of the factors (e.g., living in a mobile home, concern about injuries) that have long been believed to increase the likelihood of evacuating are more nuanced than previously believed as they decrease the likelihood of none of the household evacuating but increase the likelihood of partial household evacuation while decreasing the likelihood of complete household evacuation. This suggests that the evacuation decision making process is complex and opinions may vary within a household. Split household decisions impacts both the total number of evacuees and likely the total number of evacuating vehicles (which will be investigated by the research team shortly).

Future research could further explore partial household evacuation. In particular, researchers could investigate how differences of opinion within the household are resolved into an outcome, whether split, all stay, or all evacuate. Additionally, the composition of the staying and evacuating groups for split households could be explored to better understand the needs of those who remain behind and those who shelter elsewhere.

3.12 Acknowledgments

This work was supported by NSF grant CMMI-1520338 “Hazards SEES: Bridging Information, Uncertainty, and Decision-Making in Hurricanes using an Interdisciplinary Perspective” for which the authors are grateful. However, the authors are solely responsible for the content of this paper.

3.13 References

Alsnih, R., Rose, J. and Stopher, P., 2005. Understanding household evacuation decisions using a stated choice survey: case study of bush fires. In Transportation Research Board Annual Meeting, 84th, 2005, Washington, DC, USA.

Baker, E.J., 1991. Hurricane evacuation behavior. International journal of mass emergencies and disasters, 9(2), pp.287-310.

Bateman, J.M. and Edwards, B., 2002. Gender and evacuation: A closer look at why women are more likely to evacuate for hurricanes. Natural Hazards Review, 3(3), pp.107-117.

Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research Part B: Methodological, 37(9), pp.837-855.

Breznitz, S., 1984. Cry wolf. The psychology of false alarms. Hillsdale, NJ: LEA.

Dash, N. and Gladwin, H., 2007. Evacuation decision making and behavioral responses: Individual and household. Natural Hazards Review, 8(3), pp.69-77.

Dow, K. and Cutter, S.L., 1998. Crying wolf: Repeat responses to hurricane evacuation orders.

Dow, K. and Cutter, S.L., 2000. Public orders and personal opinions: Household strategies for hurricane risk assessment. Global Environmental Change Part B: Environmental Hazards, 2(4), pp.143-155.

Dow, K. and Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natural hazards review, 3(1), pp.12-18.

Elliott, J.R. and Pais, J., 2006. Race, class, and Hurricane Katrina: Social differences in human responses to disaster. Social science research, 35(2), pp.295-321.

Fothergill, A., 1996. Gender, risk, and disaster. International Journal of Mass Emergencies and Disasters, 14(1), pp.33-56.

Fu, H. and Wilmot, C.G., 2004. Sequential logit dynamic travel demand model for hurricane evacuation. Transportation Research Record, 1882(1), pp.19-26.

Gkritza, K. and Mannering, F.L., 2008. Mixed logit analysis of safety-belt use in single-and multi-occupant vehicles. Accident Analysis & Prevention, 40(2), pp.443-451

Gladwin, C.H., Gladwin, H. and Peacock, W.G., 2001. Modeling hurricane evacuation decisions with ethnographic methods. International Journal of Mass Emergencies and Disasters, 19(2), pp.117-143.

Hasan, S., Mesa-Arango, R. and Ukkusuri, S., 2013. A random-parameter hazard-based model to understand household evacuation timing behavior. Transportation research part C: emerging technologies, 27, pp.108-116.

Hasan, S., Mesa-Arango, R. and Ukkusuri, S., 2013. A random-parameter hazard-based model to understand household evacuation timing behavior. Transportation research part C: emerging technologies, 27, pp.108-116.

Hausman, J.A. and McFadden, D., 1981. Specification tests for the multinomial logit model.

Huang, S.K., Lindell, M.K. and Prater, C.S., 2016. Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. Environment and Behavior, 48(8), pp.991-1029.

Lim, M.B.B., Lim, H.R., Piantanakulchai, M. and Uy, F.A., 2016. A household-level flood evacuation decision model in Quezon City, Philippines. Natural Hazards, 80(3), pp.1539-1561.

Lindell, M.K., Lu, J.C. and Prater, C.S., 2005. Household decision making and evacuation in response to Hurricane Lili. Natural Hazards Review, 6(4), pp.171-179.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. and Baker, E.J., 2019. Large-scale evacuation. New York: Routledge.

McFadden, D. and Train, K., 2000. Mixed MNL models for discrete response. Journal of applied Econometrics, 15(5), pp.447-470.

Mileti, D.S. and Beck, E.M., 1975. Communication in crisis: Explaining evacuation symbolically. Communication Research, 2(1), pp.24-49.

Mileti, D.S., 1975. Natural hazard warning systems in the United States: A research assessment. Boulder, CO: Institute of Behavioral Science, University of Colorado.

National Hurricane Center (NHC). (2006). "Tropical cyclone report: 2005 Atlantic hurricane season." National Oceanic and Atmospheric Administration (NOAA), Washington, DC

Peacock, W., Morrow, B.H. and Gladwin, H., 1997. Hurricane Andrew and the reshaping of Miami: Ethnicity, gender, and the socio-political ecology of disasters. Gainsville, FL: University Press of Florida.

Perry, R.W., 1979. Evacuation decision-making in natural disasters. Mass emergencies, 4(1), pp.25-38.

Quarantelli, E.L., 1980. Evacuation Behavior and Problems: Findings and Implications from the Research Literature. OHIO STATE UNIV COLUMBUS DISASTER RESEARCH CENTER.

Quarantelli, E.L., 1980. Evacuation Behavior and Problems: Findings and Implications from the Research Literature. OHIO STATE UNIV COLUMBUS DISASTER RESEARCH CENTER.

Riad, J.K., Norris, F.H. and Ruback, R.B., 1999. Predicting evacuation in two major disasters: Risk perception, social influence, and access to resources 1. Journal of Applied Social Psychology, 29(5), pp.918-934.

Riad, J.K., Norris, F.H. and Ruback, R.B., 1999. Predicting evacuation in two major disasters: Risk perception, social influence, and access to resources 1. Journal of Applied Social Psychology, 29(5), pp.918-934.

Savitt, A. and Ge, Y. 2018. Intra-family decision making in disaster evacuations: An interdisciplinary literature review. Presented at the 2018 IRCD Researchers Meeting, Broomfield, CO.

Solís, D., Thomas, M. and Letson, D., 2010. An empirical evaluation of the determinants of household hurricane evacuation choice. Journal of Development and Agricultural Economics, 2(5), pp.188-196.

Sorensen, J. H., and Vogt-Sorenson, B. _2006_. “Community processes; Warning and evacuation.” Handbook of disaster research, H. Rodriguez, E. L. Quarantelli, and R. R. Dynes, eds., Springer, New York, 183–199.

Sorensen, J. H., and Vogt-Sorenson, B. _2006_. “Community processes; Warning and evacuation.” Handbook of disaster research, H. Rodriguez, E. L. Quarantelli, and R. R. Dynes, eds., Springer, New York, 183–199.

Thompson, R.R., Garfin, D.R. and Silver, R.C., 2017. Evacuation from natural disasters: a systematic review of the literature. Risk analysis, 37(4), pp.812-839.

Train, K. (2003). Discrete choice methods with simulation, Cambridge, University Press, Cambridge, UK

Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2011. Statistical and Econometric Methods for transportation data analysis, 2nd Ed.,

Whitehead, J.C., Edwards, B., Van Willigen, M., Maiolo, J.R., Wilson, K. and Smith, K.T., 2000. Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. Global Environmental Change Part B: Environmental Hazards, 2(4), pp.133-142.

Wilmot, C.G. and Mei, B., 2004. Comparison of alternative trip generation models for hurricane evacuation. Natural hazards review, 5(4), pp.170-178.

Appendix I

Table 3-7. Variables correlation matrix

	Injury concern	Hurricane location certainty	Age	Family cohesion	Detached home	Mobile home	Married
Injury concern	1.000						
Hurricane location certainty	-0.011	1.000					
Age	0.024	-0.019	1.000				
Family cohesion	0.008	0.052	-0.025	1.000			
Detached home	0.045	-0.031	0.077	0.077	1.000		
Mobile home	0.008	0.017	0.027	-0.068	0.224	1.000	
Married	-0.011	0.048	-0.048	0.123	0.134	0.040	1.000

CHAPTER FOUR

MODELING THE NUMBER OF HOUSEHOLD VEHICLES USED TO EVACUATE FROM HURRICANE MATTHEW WITH A ZERO TRUNCATED POISSON MODEL

Roaa Alawadi
Research Assistant
Department of Civil Engineering
Clemson University, 109 Lowry Hall, Clemson, SC 29634
Tel: 864-643-8778
Email: ralawad@clemson.edu

Ruijie Bian
Postdoctoral Researcher
Department of Civil Engineering
Clemson University, 109 Lowry Hall, Clemson, SC 29634
Tel: 225-354-6193
Email: rbian@clemson.edu

Pamela Murray-Tuite
Associate Professor
Department of Civil Engineering
Clemson University, 109 Lowry Hall, Clemson, SC 29634
Tel: 864-656-3802
Email: pmmurra@clemson.edu
ORCID: 0000-0003-3079-289X

Satish V. Ukkusuri
Professor
Lyles School of Civil Engineering
Purdue University, 550 Stadium Mall Drive, West Lafayette, IN 47907
Tel: (765) 494-2296
Email: sukkusur@purdue.edu

Yue Ge
Assistant Professor
School of Public Administration
University of Central Florida, 12494 University Blvd., Orlando, FL 32816
Tel: 407-823-4376
Email: yue.ge@ucf.edu

Dr. Ruijie Bian contributed with the model choice as well as the comparison between modeled and observed number of vehicles used in evacuation. Dr. Pamela Murray-Tuite revised the overall paper content as well as her guidance in the hypotheses adopted and literature review. Both Dr. Ukkusuri and Dr. Ge reviewed the overall paper content and provided their input of previous literature.

.

4.1 Abstract

This paper investigates the number of household vehicles used in evacuation for Hurricane Matthew. Zero truncated Poisson regression was utilized in this study with survey data from the Jacksonville, FL metropolitan area. This modeling approach has rarely been applied to the evacuation context and the prediction of the number of household vehicles used is relatively understudied, compared to other evacuation-related decisions. The final preferred model contains three significant variables (marital status, gender, and evacuation timing from 6 am to noon). Evacuation timing from 6 am to noon and gender were found to have negative effects on the number of vehicles used by households in evacuation. Being married had a positive effect on the number of household vehicles used in evacuation. The final preferred model has a good fit with a Pseudo R-squared of 0.46. The model under-estimated the use of one and four vehicles and over-estimated the use of two, three, and five vehicles. Overall, the model estimated 11 more vehicles (3% more) than were observed. This model can be used for planning the transportation vehicular needs in evacuation in consideration with other variables at the zonal level.

Keywords: Hurricane evacuation; Household vehicles; Zero truncated Poisson regression; Hurricane Matthew

4.2 Introduction

Hurricanes are considered among the deadliest natural hazards, with an increase to 116 in the average annual fatalities related between 2001 and 2010 [National Oceanic and Atmospheric Administration (NOAA) 2011]. Hurricane Matthew was one of the deadliest Atlantic storms since Katrina in 2005 and led to one of the largest recent hurricane evacuations along the Southeastern coast of the United States (Martín et al. 2017). The goal of the evacuation process is to avoid injuries, loss of life, and a lower property damage and economic loss. A main objective of evacuation is to move the evacuees from the danger zone as quickly and safely as possible (Lindell et al. 2019). For successful evacuation planning it is important to determine the evacuation demand; where evacuation demand is governed by many factors, such as hurricane trajectory and household characteristics (Baker 1991).

During an evacuation process, households make a series of evacuation-related decisions: whether to evacuate or not, when to evacuate, where to evacuate, which mode to use, and the number of vehicles to use in the evacuation, among other decisions. This decision making process is complex in nature and it is important to understand how these decisions are made to plan and implement successful hurricane evacuation.

The main focus of this paper is to better understand the factors affecting household choice of the number of household vehicles used in evacuation. This will allow a better prediction of the number of evacuating vehicles; and thus a better overall evacuation vehicle demand estimation. From a planning perspective, understanding the vehicular needs and how they vary across the different geographical levels can significant impact evacuation efficiency. Personal vehicles are by far the most preferred evacuation mode of transportation (Lindell et al. 2019). Many studies presented a relatively wide range of the number of household vehicles used in evacuation. For example, Lindell et al. (2011) reported a range of (1.10 – 2.15) vehicles used by households across counties in Hurricane Lili. When taking into account the total number of evacuating households, this range allows for a huge difference in the predicted number of vehicles, which makes it necessary to provide a better prediction modeling.

This study tests potential factors affecting household vehicle choice, taking into account socio-economic and demographic factors, living in a risk area, receiving evacuation notices, housing type, past hurricane experience, evacuation timing, family cohesion, hurricane information certainty, and whether household members evacuated partially or fully. Data for this study comes from a mail survey of Jacksonville, Florida residents after Hurricane Matthew. Survey responses show that the majority of respondents used personal vehicles in evacuation, only five respondents reported using other modes of transportation. Zero truncated Poisson regression was utilized to model the number of household vehicles used for evacuation along with the significant predictors of the vehicle choice.

The remainder of this paper is organized into five sections. The first section presents a selection of related literature and hypotheses investigated in this study. The second and third sections discuss the data and modeling methodology. The fourth section presents results of the study and discussion of the findings. The final portion provides conclusions and suggestions for future research.

4.3 Literature Review and Hypotheses

There are three main travel modes used in large scale evacuations: personal vehicles, carpooling and official transportation (school buses or transit agencies) (Lindell et al. 2019). In some cases agencies used aircraft, postal vehicles, trains, or even fire trucks for very localized flooding (Perry et al. 1981). However, personal vehicles are the dominant mode of transportation used in large scale evacuations in the United States. Based on prior surveys, percentages of personal vehicle usage in hurricane evacuation are 90% in Hurricane Lili (Lindell et al. 2011), 89% in Hurricane Katrina (Wu et al. 2012), and 87% in Hurricane Ike (Wu et al. 2013). Even though existing research emphasizes having the household together during evacuations, this does not necessarily mean that households will evacuate in one vehicle (Dow and Cutter 2002). According to Dow and Cutter (2002), 25% of households used multiple vehicles in evacuation. Households used an average of 1.26 vehicles to evacuate from Hurricane Floyd (Dow and Cutter 2002), 1.42 vehicles in Katrina/ Rita (Wu et al. 2012), and 1.25 vehicles in Ike (Wu et al. 2013). Lindell et al. (2011) reported a range of 1.10 – 2.15 vehicles across counties for Hurricane Lili. The wide range of vehicles usage in hurricane evacuation is problematic for evacuation planners, with a difference of over 1 million vehicles in an evacuation of 1 million households (Yin et al. 2014).

Some studies did not present their methods for estimating the number of evacuating vehicles per household while others reported the average from survey results (Lindell and Prater 2007). Different approaches used in the estimation of household evacuating vehicles include subjective assumptions (Radwan et al. 1985), stated preference surveys (Ruch and Schumann 1997), revealed preference surveys (Lindell et al. 2002; Prater et al. 2000; Dow and Cutter 2002; Siebeneck and Cova 2008; Wu et al. 2012; and Lindell et al. 2011). Other methods include simulation based on a Poisson distribution (Cova and Johnson 2002) and Poisson models with exposure and right-censored Poisson regression (Yin et al. 2014) developed with revealed preference surveys.

Only a minority of households ride with others (Lindell et al. 2019). Only 5% of households asked for assistance from others, most of them evacuated by riding with others (Baker 2000b). Wu et al. (2012) found that the lack of vehicle access, and thus more carpooling, was more common among those with any of the following characteristics: older, unmarried, residents with low education and income.

The predictors of the number of household evacuating vehicles were studied in a few prior works. It was found that larger households and those with more income took more cars (Dow and Cutter 2002). These findings are relatively intuitive since larger households may need more than one vehicle to evacuate comfortably, and those with higher income are more likely to own more vehicles and evacuate with them to keep the vehicles from being damaged by the hurricane (Dow and Cutter 2002). Wu et al. (2012) reported that married households took more vehicles in the evacuations for Hurricanes Rita and Katrina. Similarly other factors such as hurricane experience and receiving mandatory evacuation orders were found to have a positive effect on household usage of vehicles in evacuation (Yin et al. 2014). Dow and Cutter (2002) provided reasons for households using more vehicles in evacuation. It could be explained by job responsibilities that might require one household member to return sooner than others, or residents took many possessions with them, or they want the flexibility to allow one member to return to cleanup while others stay with children. Other indicators of car usage in evacuation along with their effect are presented in Table 4-1.

Table 4-1. Predictors of vehicle usage in evacuations.

Predictor	**Effect**	**Source**
Larger household	+	Dow and Cutter (2002); Wu et al. (2012); Yin et al. (2014)
Higher income	+	Dow and Cutter (2002); Wu et al. (2012)
Proximity to water (closer)	-	Yin et al. (2014)
Married	+	Wu et al. (2012)
Travel distance (more)	-	Yin et al. (2014)
Mandatory evacuation order	+	Yin et al. (2014)
Non-mandatory evacuation order	-	Yin et al. (2014)

Hurricane experience	+	Yin et al. (2014)
Number of elderly household members over 80 years.	-	Yin et al. (2014)
Number of household members aged (18-80) years	+	Yin et al. (2014)
Pet ownership	+	Yin et al. (2014)
Evacuation to friends/ relative house	-	Yin et al. (2014)
Living in a mobile home	+	Yin et al. (2014)

4.4 Hypotheses

As a starting point of this study, a number of hypotheses were adopted for the initial selection of variables to be examined.

H1: Marital status (married) is positively related to the number of vehicles used by a household in evacuation.

Wu et al. (2012) concluded that married household members are more likely to use more vehicles in evacuation. Another study by Maghelal et al. (2016) noted that some households evacuate in separate groups. Married respondents may have larger families than single respondents, which could indicate a greater number of household vehicles and/or require more vehicles to accommodate the family.

H2: Morning (6 am– noon) evacuation departure timing is positively related to the number of vehicles used by a household in evacuation.

Lindell et al. (2019) stated that in Hurricane Ike, there were consistent spikes of evacuation departure time during the late morning (6 am – 12 pm) and afternoon followed by a substantial decrease in the evening. Early departures are a sign that people want sufficient day-time for evacuation and allow multiple vehicles; whereas later departure times could result in fatigue.

H3: More certainty about when to evacuate is positively related to the number of vehicles used by a household in evacuation.

Murray-Tuite et al. (2012) stated that more households depart closer to the day of hurricane landfall. Less certainty about evacuation timing may lead households not to evacuate early. Departing close to the day of hurricane landfall often results in severe congestion (Murray-Tuite et al. 2012), which may encourage households to travel together in the congested situations.

H4: Partial household evacuation is negatively related to the number of vehicles used by a household in evacuation.

Dow and Cutter (2002), Wu et al. (2012), and Yin et al. (2014) all studied the household size's effect on the number of vehicles used in household evacuation. These studies reported a positive relation between the household size and the number of vehicles. However, if a household evacuates partially, with some household members remaining behind, a vehicle may remain with them. Thus, fewer household vehicles would be used in the evacuation.

4.5 Data

After the 2016 Hurricane Matthew, a household survey was conducted in the metropolitan area of Jacksonville, Florida during the summer and fall in 2017. Four waves of mailings (i.e., three complete survey packets and a postcard reminder) were implemented using the standard procedure recommended by Dillman, Smyth, and Christian (2014). In each wave, the survey questionnaire was assembled into four different versions where the four major blocks of questions (i.e., uncertainty factors and evacuation behaviors, social network information, intra-family decision making factors, and information sources) were placed in different sequences with household demographic questions at the end to avoid potential low response rates for questions at the latter part of the survey. In other words, for each wave four batches of the survey were mailed to the four quarters of the sampled households. The same survey questionnaire was also made available for respondents to complete online at SurveyMonkey.com if one preferred web entries with a given survey ID for each questionnaire in the mail. In total, 588 individual responses were deemed valid in the data analysis.

Table 4-2 presents summary statistics of the explanatory variables considered for the model.

Table 4-2. Summary statistics of the selected explanatory variables (unweighted values).

Variable	**Min-imum**	**Max-imum**	**Mean**	**Standard deviation**
Dependent Variable				
Number of household vehicles used in evacuation	1	4	1.34	0.653
Independent Variables				
Respondent Characteristics				
Previously evacuated (0: No; 1: Yes)	0	1	0.40	0.49
Married (0: no; 1: yes)	0	1	0.72	0.45
Race black (0: No; 1: Yes)	0	1	0.01	0.08
Race white (0: No; 1: Yes)	0	1	0.9	0.30
Respondent Age (20 to 92 years)	20	92	57.97	14.13
Gender (0: Female; 1: Male)	0	1	0.41	0.49
Household Characteristics				
Total number of household members	1	7	2.32	1.143
Number of household members under 18 years old	0	6	0.69	1.08
Number of household members 18 - 65 years old	0	6	1.65	0.98
Number of household members over 65 years old	0	2	1.21	0.82
Number of household members with medical conditions	0	1	0.18	0.38
Income (more than 60,000 US dollars). (0: No; 1: Yes)	0	1	0.66	0.476
Family cohesion level (1-5; 1: low, 5: High)	1	5	4.50	0.81
Home Characteristics				
Living in single family detached homes (0: no; 1: yes)	0	1	0.88	0.32

Living in mobile homes (0: no; 1: yes)	0	1	0.03	0.17
Distance to coast (miles)	0	56	10.46	12.62
Number of years in current home	0	63	14.13	12.24
Number of years in current community	0	74	19.20	16.28
Concern and Certainty				
Injury concern (Risk perception); (1-5; 1: smallest, 5: highest)	1	5	2.22	1.25
Certainty about hurricane impact location (1: not certain, 5: extremely certain)	1	5	3.75	1.10
Certainty about whether they live in an evacuation zone (1: not certain, 5: extremely certain)	1	5	4.37	1.15
Certainty about time of hurricane impact (1: not certain, 5: extremely certain)	1	5	3.87	1.13
Certainty about time needed to prepare for evacuation (1: not certain, 5: extremely certain)	1	5	3.94	1.11
Certainty about when to evacuate (1: not certain, 5: extremely certain)	1	5	3.94	1.15
Certainty about evacuation destination (1: not certain, 5: extremely certain)	1	5	4.16	1.29
Certainty about evacuation route (1: not certain, 5: extremely certain)	1	5	4.29	1.05
Evacuation Details				
Evacuation on the day of highest impact (0: No; 1: Yes)	0	1	0.04	0.20
Evacuation 1 day before highest impact (0: No; 1: Yes)	0	1	0.40	0.20
Evacuation 2 days before highest impact (0: No; 1: Yes)	0	1	0.35	0.48
Evacuation 3 days before highest impact (0: No; 1: Yes)	0	1	0.19	0.39
Evacuation timing (from midnight to 6 am) (0: No; 1: Yes)	0	1	0.04	0.19
Evacuation timing (6 am to noon). (0: No; 1: Yes)	0	1	0.36	0.48
Evacuation timing (noon to 6 pm). (0: No; 1: Yes)	0	1	0.31	0.46
Evacuation timing (6 pm to midnight). (0: No; 1: Yes)	0	1	0.130	0.340
Household Partially evacuated (0: No; 1: Yes)	0	1	0.060	0.244
Evacuation distance (Miles)	0	880	126.11	143.99

As shown in Table 4-3, the sample is biased towards certain demographic characteristics,. To address this bias, we used rake weighting. Rake weighting is basically applying weights based on certain demographic characteristics in the data sample based on the overall population (Pew Research 2018). In this study, the rake weighting was based on three demographic variables: gender (male or female), education level (four-year college degree or lack thereof), and age group (18 through 44, 45 through 59, and 60+). These variables are not correlated, which is a requirement of the raking process.

Table 4-3.Demographic distributions of the data sample and the 2016 population of Jacksonville, FL (ACS 2018)

Attribute	Category	Population	Sample	Bias	Average bias
Age group	**18 to 44**	0.50	0.13	0.37	0.24
	45 to 59	0.26	0.34	0.08	
	60 or over	0.24	0.53	0.29	
Education level	**no four-year college degree**	0.73	0.27	0.46	0.45
	four-year college degree	0.27	0.72	0.45	
Gender	**female**	0.52	0.63	0.11	0.11
	male	0.48	0.37	0.11	
Income (annual)	**less than $15,000**	0.12	0.04	0.08	0.08
	$15,000 to $30,000	0.15	0.07	0.08	
	$30,000 to $45,000	0.16	0.08	0.08	
	$45,000 to $60,000	0.14	0.15	0.01	
	$60,000 to $100,000	0.24	0.26	0.02	
	over $100,000	0.19	0.40	0.21	
Marital status	**not married**	0.54	0.23	0.31	0.31
	married	0.46	0.77	0.31	

Two additional demographic variables (income level, marital status) were used to test whether the raking reduced the bias outside of the raking variables themselves (Table 4-4) (Pew Research 2018). From the calculations we conclude than the sample bias was reduced by 16.5%.

Table 4-4. Evaluation of bias before and after rake weighting based on marital status and income.

Marital status	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
Not married	0.54	0.23	0.31	0.57	0.03	-0.28
married	0.46	0.77	0.31	0.43	0.03	-0.28
Average			0.31		0.03	-0.28
Income level	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
1	0.12	0.04	0.08	0.11	0.01	-0.07
2	0.15	0.07	0.08	0.11	0.04	-0.04
3	0.16	0.08	0.08	0.13	0.03	-0.05
4	0.14	0.15	0.01	0.15	0.01	0.00
5	0.24	0.26	0.02	0.23	0.01	-0.01
6	0.19	0.40	0.21	0.27	0.08	-0.13
Average			0.08		0.03	-0.05
	Initial bias	**Weighted bias**	**Bias change**			
Overall	0.195	0.03	-0.165			

4.6 Methodology

In this study, the number of vehicles used by an evacuating household is investigated with Poisson-based models. Poisson regression is used for count data (e.g., number of vehicles). The Hurdle Poisson regression was first tested. This type of regression presents two models, one is a logit regression model for the zero counts (whether households used personal vehicles to evacuate or not). The other model is a truncated Poisson regression for the positive count (number of household vehicles used in evacuation) (Cragg 1971). However, in our data set the vast majority of households used personal vehicles; only five respondents reported not using personal vehicles. This was considered too few observations of one outcome to use the logit model, making the Hurdle Poisson model impractical for this dataset. Zero Truncated Poisson regression was selected as the modeling technique (and the five respondents not using personal vehicles were excluded from the modeling dataset). In the zero truncated regression, the response variable cannot have a value of zero (Zuur et al. 2009). The underlying mathematics for zero-truncated Poisson models is presented in this section.

The starting point was the Poisson probability function shown in equation (1) (Zuur et al. 2009):

$$f\ (y_i; \mu_i\ |y_i \geq\ 0) = \frac{\mu^{yi} \times e^{-\mu_i}}{y_i\,!} \tag{1}$$

Where
Y_i= response variable for observation i.

μ_i = mean of the Poisson distributed response variable.

y_i = possible outcome of Y_i.

Equation (1) gives the probability for each integer value of y_i that is equal or larger than 0 for a given mean μ_i. To exclude the probability that y_i = 0 from the Poisson distribution, Equation (1) is divided by by 1 minus the probability that y_i = 0, resulting in Equation (2) (Zuur et al. 2009):

$$f\ (y_i; \mu_i\ |y_i >\ 0) = \frac{\mu^{yi} \times e^{-\mu_i}}{(1-e^{-\mu_i}) \times y_i!} \tag{2}$$

From this step on, the truncated Poisson generalized linear model follows the ordinary Poisson generalized linear model. The same mean and variance relationships are used, also the same systematic component, and the same link function. Hence, the mean value μ_i is modelled as an exponential function of the predictor function, as shown in Equation (3) (Zuur et al. 2009):

$$\mu_i =\ e^{\alpha+\beta_1+X_{1i}+\cdots+\beta_q+X_{1q}} \tag{3}$$

Specification of a likelihood criterion is needed in order to find the regression parameters. Using the probability function in Equation (2) gives the likelihood function in Equation (4) (Zuur et al. 2009):

$$L =\ \Pi_i\ f\ (y_i; \mu_i\ |y_i >\ 0) = \Pi_i\, \frac{\mu^{yi} \times e^{-\mu_i}}{(1-e^{-\mu_i}) \times y_i!} \tag{4}$$

The principle of maximum likelihood states that for the given data, maximizing L as a function of the regression parameters is needed. To aid the numerical optimization routines, the log likelihood is used to work with a sum instead of a product, as shown in Equation (5) (Zuur et al. 2009):

$$Log(L) = \sum_i \log\big(f\ (y_i; \mu_i\ |y_i > 0)\big) = \sum_i \log\left(\frac{\mu_i^{y_i} \times e^{-\mu_i}}{(1-e^{-\mu_i}) \times y_i!}\right) \tag{5}$$

Using matrix notation, $\beta_1 + X_{1i} + \cdots + \beta_q + X_{qi}$ is replaced by $\boldsymbol{X_i} \times \boldsymbol{\beta}$, where $\beta = (\beta_1, \ldots, \beta_q)$ and X_i contains all explanatory variables for observation i. This leads to equation (6) (Zuur et al. 2009):

$$Log(L) = -\sum_i e^{x_i \times \beta} + \sum_i y_i \times X_i \times \beta - \sum_i \log\big(1 - e^{X_i \times \beta}\big) - \sum_i \log\left(\Gamma\big(y_i + 1\big)\right) \tag{6}$$

Represented earlier is maximum likelihood criterion that needs to be maximized as a function of the regression parameters. Equation (6) can be fitted by maximizing the likelihood directly, for example using a Newton–Raphson procedure. This method is incorporated in Poisson regression routines where it is possible to specify truncation (e.g., the computer program LIMDEP (Greene, 1998)).

Initial variables were selected based on previous evacuation literature and the previously stated hypotheses. A zero truncated Poisson model was developed based on a number of trials where all the variables in Table 2 were examined. In each iteration a variable was added to the model and tested for significance among other variables in a forward step-wise fashion. Variables were considered significant if their p-value was 0.1 or less. Correlation was tested between variables, and no factors with correlation of 0.3 or more were considered in the same model as shown in Table 4-5.

Table 4-5. Explanatory Variables Correlation Matrix.

	Married	Gender	Evacuation timing (6 am – noon)
Married	1.000		
Gender	0.207	1.000	
Evacuation timing (6 am – noon)	-0.010	-0.087	1.000

4.7 Results and Discussion

The preferred zero truncated Poisson model has 238 observations. McFadden Pseudo R-squared is used to test the goodness of fit, because Poisson regression is also estimated by maximum likelihood (Greene 2002). Our model has Pseudo R-squared 0.46 which represents an a good fit of the current model specification (McFadden 1977).

Table 4-6 shows the regression model results. The model contains three significant variables (married, evacuation timing from 6 am to noon, and gender). Married has a positive coefficient of (0.087), evacuation timing from (6 am to noon) has a negative coefficient of (-0.729), and gender has a negative coefficient of (-0.559).

Table 4-6. Final Zero Truncated Poison model of household number of vehicles used in evacuation.

Variable description	**Coefficient**	**Standard error**
Constant	-0.680 ***	0.206
Married	0.807***	0.253
Evacuation timing (6 am – noon)	-0.729**	0.301
Gender	-0.559**	0.250
Model Statistics		
Number of Observations	238	
McFadden Pseudo R-Squared	0.456	
Chi squared	262.768	
Note: ***, **, * ⟹ Significance at 1%, 5%, 10%		

A way to assess the zero truncated model fit is to compare the count variable observed in the data with the estimated by the model (Van Der Heijden et al. 2003) as shown in Figure4-1. The model estimates for each number of used vehicles used is close to the number of vehicles observed. However some estimations of the model are underestimated compared to observed numbers (one vehicle, four vehicles). Other model predictions of the number of vehicles are over estimated (two vehicles, three vehicles, and five vehicles). The total number of observed vehicles is 318 vehicles, while the zero truncated model predicted 329 vehicles.

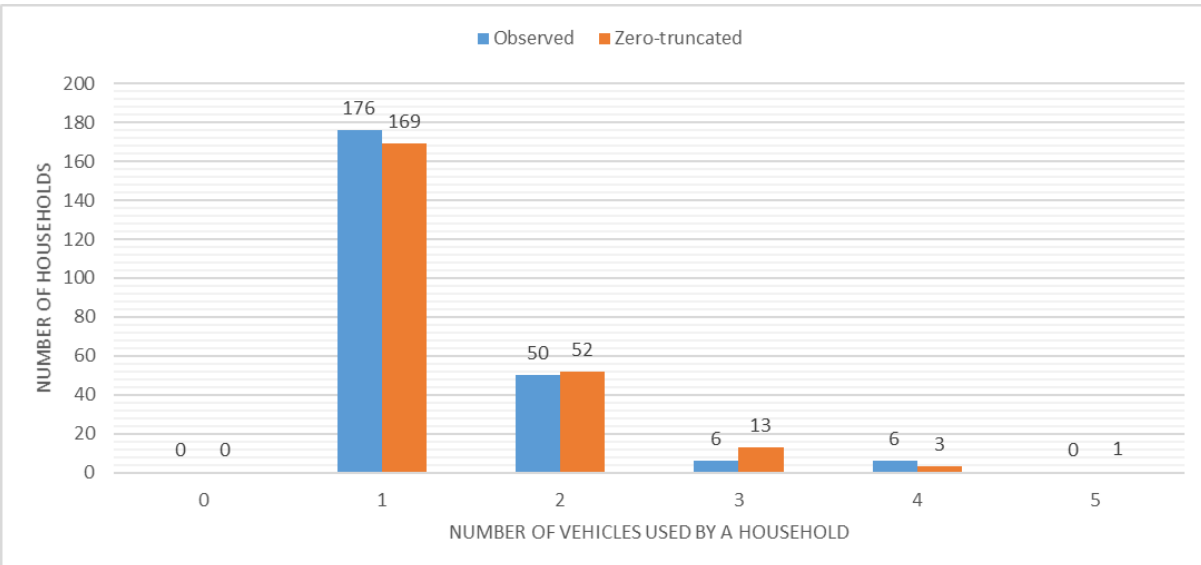

Figure 4-1: Observed and estimated counts of household vehicles used in evacuation

H1: Marital status (Married) is positively related to the number of vehicles used by a household in evacuation.

This hypothesis is supported. In our model married household members has a positive effect on the number of vehicles used in evacuation. These findings are consistent with Wu et al. (2012).

H2: Evacuation timing from (6 am– Noon) in positively related to the number of vehicles used by a household in evacuation.

This hypothesis is not supported. In our model evacuation timing from (6 am – noon) has a negative effect on the household number of vehicles used for evacuation. Lindell et al. (2019) stated that evacuation spikes occur in the late morning; which may result in routes congestion. This may encourage households to travel compactly in fewer vehicles.

H3: More certainty about when to evacuate is positively related to the number of vehicles used by a household in evacuation.

This hypothesis is not supported. Certainty about evacuation timing is not significant in this study. However, it is important to test the effect of household certainty in terms of vehicle choice (see Appendix 2). Similarly, certainty about hurricane impact location, impact timing, living in an evacuation zone, preparation time, destination, and route were non-significant.

H4: Partial household evacuation is negatively related to the number of vehicles used by a household in evacuation.

Results for this hypothesis are somewhat mixed. The partial household evacuation variable is not presented in the final preferred model. However, it is significant when tested alone, and has a negative effect on the number of household evacuating vehicles (see Appendix 1). Testing this variable is important enough in order to further investigate the effect of partial evacuation on vehicle choice.

4.8 Conclusions and Future Directions

This paper investigates the number of household vehicles used in evacuation for Hurricane Matthew. The significance of this study comes from the need to anticipate the total number of vehicles used in an evacuation to properly plan traffic management and mitigation strategies as well as for fuel needs. Current studies present a range of evacuating household vehicle numbers, but this could lead to a vast difference when taking into account the total number of evacuating households.

Zero truncated Poisson regression was utilized in this study. The final preferred model has an excellent fit with a McFadden Pseudo R-squared 0.46. Model estimation of household evacuating vehicles was compared to the observed number of vehicles from the survey. Some estimations of the model were underestimated compared to observed numbers (one vehicle, four vehicles). Other model predictions of the number of vehicles were overestimated (two vehicles, three vehicles, and five vehicles). Overall, the model estimated 11 more vehicles (3% more) than were observed. A slight over-estimate is reasonable for planning purposes.

The final model contains three significant variables (marital status, gender, and evacuation timing from 6 am to noon). (Another model show partial household evacuation parameter significant when tested alone as an indicator of household vehicle usage, but in the multivariable context, it was non-significant.) Evacuation timing from 6 am to noon and gender were found to have negative effects on the number of vehicles used by households in evacuation. Being married had a positive effect on the number of household vehicles used in evacuation. Among these variables, marital status and housing type were previously studied and our findings are consistent with this prior work (Wu et al. 2012; Yin et al. 2014). Examining partial household evacuation, evacuation timing, and evacuation certainty variables is considered new in the context of this study.

This study contributes to the relatively small body of literature examining factors influencing the number of household vehicles used in an evacuation. It is among the first to use a zero truncated Poisson model in the evacuation context. The findings of this study provide deeper insight for evacuation managers about indicators to be considered while preparing more comprehensive evacuation plans. This could enhance evacuation demand estimation thus a better traffic management plan.

Future research could further explore partial household evacuation as an indicator of the number of household vehicles used in evacuation, since this variable was not studied previously in this context and had mixed significance in our study (significant in the individual variable model but non-significant in the multivariable model). It is important to better understand the factors leading a household to partially or fully evacuate since these factors could affect the number of household evacuating vehicles.

This paper included the study of household evacuating personal vehicles exclusively. Other modes of evacuation transportation were not studied. It would be beneficial to consider other modes of evacuation in future studies able to capture a large split in mode choice. Another future direction is to further investigate the motives behind using multiple household vehicles for evacuation. This helps to better understand the complex process of evacuation decision making and hence, better evacuation demand estimation and better evacuation planning.

4.9 Acknowledgments

This work was supported by NSF grant CMMI-1520338 “Hazards SEES: Bridging Information, Uncertainty, and Decision-Making in Hurricanes using an Interdisciplinary Perspective” for which the authors are grateful. However, the authors are solely responsible for the content of this paper.

4.10 References

Baker, E.J., 2000. Hurricane evacuation in the United States. Storms, 1, pp.306-319.

Cova, T., and Johnson, J. (2002). "Microsimulation of neighborhood evacuations in the urban wildland interface." Environ. Plann. A, 34(12), 2211–2229.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica (pre-1986), 39(5), p.829.

Dow, K. and Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natural hazards review, 3(1), pp.12-18.

Greene, W.H., 1998. Limdep.

Greene, W.H., 2002. LIMDEP, version 8.0. Econometric Modeling Guide, Vol 1. Plainview, NY: Econometric Software. Inc., pp. E14-9-E14-11.

Lindell, M.K., Kang, J.E. and Prater, C.S., 2011. The logistics of household hurricane evacuation. Natural hazards, 58(3), pp.1093-1109.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. and Baker, E.J., 2019. Large-scale evacuation. New York: Routledge.

Lindell, M.K. and Prater, C.S., 2007. Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: Examples from hurricane research and planning. Journal of Urban Planning and Development, 133(1), pp.18-29.

Lindell, M., Prater, C., and Wu, J. (2002). Hurricane evacuation time estimates for the Texas Gulf Coast, Texas A&M Univ., College Station, TX.

Maghelal, P., Peacock, W.G. and Li, X., 2016. Evacuating together or separately: factors influencing split evacuations prior to Hurricane Rita. Natural Hazards Review, 18(2), p.04016008.

Martín, Y., Li, Z. and Cutter, S.L., 2017. Leveraging Twitter to gauge evacuation compliance: Spatiotemporal analysis of Hurricane Matthew. PLoS one, 12(7), p.e0181701.

National Oceanic and Atmospheric Administration (NOAA). (2011).

McFadden, D., 1977. Quantitative methods for analyzing travel behavior of individuals: some recent developments. Berkeley: Institute of Transportation Studies, University of California.

Perry, R.W., Lindell, M.K. and Greene, M.R., 1981. Evacuation planning in emergency management

Prater, C., Wenger, D., and Grady, K. (2000). Hurricane Bret post-storm assessment: A review of the utilization of hurricane evacuation studies and information dissemination, Texas A&M Univ. Hazard Reduction and Recovery Center, College Station, TX.

Radwan, A., Hobeika, A., and Sivasailam, D. (1985). “Computer simulation model for rural network evaluation under natural disasters.” ITE J., 55(9), 25–30.

Ruch, C., and Schumann, G. (1997). Corpus Christi study area hurricane contingency planning guide, Texas A&M Univ., Hazard Reduction and Recovery Center, College Station, TX.

Siebeneck, L., and Cova, T. (2008). “An assessment of the return-entry process for Hurricane Rita 2005.” Int. J. Mass Emergencies Disasters, 26, 91–111.

Thompson, R.R., Garfin, D.R. and Silver, R.C., 2017. Evacuation from natural disasters: a systematic review of the literature. Risk analysis, 37(4), pp.812-839.

Van Der Heijden, P.G., Cruyff, M. and Van Houwelingen, H.C., 2003. Estimating the size of a criminal population from police records using the truncated Poisson regression model. Statistica Neerlandica, 57(3), pp.289-304.

Wu, H.C., Lindell, M.K. and Prater, C.S., 2012. Logistics of hurricane evacuation in Hurricanes Katrina and Rita. Transportation research part F: traffic psychology and behaviour, 15(4), pp.445-461.

Wu, H.C., Lindell, M.K., Prater, C.S. and Huang, S.K., 2013. Logistics of hurricane evacuation in Hurricane Ike. Logistics: perspectives, approaches and challenges. Nova Science, Hauppauge, pp.127-140.

Yin, W., Murray-Tuite, P. and Gladwin, H., 2014. Statistical analysis of the number of household vehicles used for Hurricane Ivan evacuation. Journal of Transportation Engineering, 140(12), p.04014060.

Yin, W., Murray-Tuite, P.M., Ukkusuri, S.V., Galdwin, H. 2014b. Pre-evacuation activities for hurricane evacuation: an analysis of behavioral intentions from Miami Beach, Florida. 93rd Annual Meeting of the Transportation Research Board, Washington, DC.

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A. and Smith, G.M., 2009. Zero-truncated and zero-inflated models for count data. In Mixed effects models and extensions in ecology with R (pp. 261-293). Springer, New York, NY.

4.11 Appendix I

Table 4-7. Zero Truncated Poison model of household number of vehicles used in evacuation.

Variable description	**Coefficient**	**Standered error**
Constant	-0.645 ***	0.214
Married	0.794***	0.253
Evacuation timing (6 am – noon)	-0.713**	0.302
Gender	-0.583**	0.253
Partial household evacuation	-0.214	0.416
Model Statistics		
Number of Observations	238	
McFadden Pseudo R-Squared	0.456	
Note: ***, **, * ⟹ Significance at 1%, 5%, 10%		

Table 4-8. Unweighted Zero Truncated Poison model of household number of vehicles used in evacuation.

Variable description	**coefficient**	**Slandered error**
Partial household evacuation	-2.036**	.989
Model Statistics		
Number of Observations	238	
Note: ***, **, * ⟹ Significance at 1%, 5%, 10%		

4.12 Appendix II

Table 4-9. Zero Truncated Poison model of household number of vehicles used in evacuation.

Variable description	**Coefficient**	**Standered error**
constant	-0.691 ***	0.201
Married	0.831***	0.252
Evacuation timing (6 am – noon)	-0.731**	0.301
Gender	-0.529**	0.249
Certainty about evacuation timing	0.0021	0.002
Model Statistics		
Number of Observations	238	
McFadden Pseudo R-Squared	0.46	
Note: ***, **, * ⟹ Significance at 1%, 5%, 10%		

CHAPTER FIVE

DETERMINANTS OF DEPARTURE TIMING AND THE DEPARTURE TIMING LEARNING EXPERIENCE OF HOUSEHOLDS IN HURRICANE MATTHEW

Roaa Alawadi[a] , Pamela Murray-Tuite[b] , Ruijie Bian[c]
[a] Research Assistant, Glenn Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 864-643-8778; Email: ralawad@clemson.edu

[b] Associate Professor, Glenn Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 864-656-3802; Email: pmmurra@clemson.edu

[c] Postdoctoral Researcher, Department of Civil Engineering, Clemson University, 109 Lowry Hall, Clemson, SC 29634; Tel: 225-354-6193; Email: rbian@clemson.edu

Dr. Pamela Murray-Tuite revised the overall paper content as well as her guidance in the hypotheses adopted and literature review. Dr. Ruijie Bian contributed with the model choice as well as the comparison between modeled and observed cumulative number of households departed at each time interval.

5.1 ABSTRACT

This paper investigates the factors affecting departure timing choice of households from Hurricane Matthew, where the choice of departure time during disasters is a complex dynamic process, and having an accurate estimate of the departure time will allow the prediction of dynamic evacuation demand and developing effective evacuation strategies which will eventually enhance the overall evacuation planning and management. A Cox proportional-hazards model was utilized to model the evacuation departure timing; Four significant variables were identified in the final model, of which two of them are factors related to uncertainty and how it effects departure timing choice. This paper also studies the actual departure timing of evacuees and their stated preference about whether or not they would change their evacuation timing if they relived the hurricane event. This part of the study improves the understanding and predicting of households behavior, which is considered one of the significant aspects of hurricane evacuation research. A Binary Logit model

was utilized in this part and the preferred model contains five significant variables related to past experience, the type of evacuation order received, and the evacuation destination.

Keywords: Hurricane evacuation; Departure timing; Cox proportional model; Hurricane Matthew; Change departure timing; Binary Logit model; Uncertainty.

5.2 INTRODUCTION

Evacuations, in general, include the relocation of perhaps millions of people travelling tens or hundreds of miles in vehicles (Lindell, Murray-Tuite et al. 2019). Mass evacuations are common; over a 10-year period, evacuations involving 1,000 or more persons occur, on average, about every two weeks somewhere in the United States (Dotson and Jones 2005). The combination of the number of evacuating vehicles, the urgency and timing at which they leave, and the road configuration and operations heavily influence the overall network clearance and individually experienced evacuation time.

This paper focuses on the departure time decision. Conceptually based on Urbanik et. al's (1980) model for evacuation time and Lindell and Perry's (2012) protective action decision model (PADM), departure time is based on a variety of factors including the time to perceive that a hazard exists, time to assess whether one would be affected by the hazard, time to assess the potential effectiveness of protective action alternatives in reducing risk, time to select an alternative (e.g., evacuate), and time to prepare to evacuate. Even after the individual or household is prepared to evacuate, time of day may then play a role (as people tend to prefer to leave during daylight (Lindell et al., 2019)) as well as the anticipated time to reach the destination and the transportation system characteristics (Hasan et al. 2013). All of these individual times can be affected by a variety of factors, adding to the complexity.

Experience may influence the values of these factors in a future evacuation and possibly the choices themselves. However, the role of experience is not necessarily straightforward

(Lindell, Murray-Tuite et al. 2019). A special case relating to experience is a previous "unnecessary" evacuation for a disaster that failed to occur or that struck elsewhere. Authorities may be concerned that people who are told to evacuate during one or more events and do so without the disaster striking near them, will be less likely to do so in future events – the "cry wolf" effect. However, little empirical evidence exists that the cry wolf effect has been realized; in fact, one area of Florida evacuated three times in one season without a direct strike without a significant decline in evacuation rates (Lindell, Murray-Tuite et al. 2019). Although, the evacuation rates may not be significantly affected, other aspects, such as departure timing intentions for a future hurricane may warrant additional exploration.

Departure time may also be influenced by uncertainty. For example, uncertainty about the hurricane's impact location may prolong the assessment of whether the hazard applies to an individual and how well evacuation would mitigate the risk and delaying the decision to evacuate as potential evacuees wait for additional forecast and warning information. The hurricane's track uncertainty may also affect how certain the potential evacuees are about where to go and the route by which to get there. The statistical significance of certainty as a factor for departure time is examined in this study as a new contribution to the factors considered in the literature.

Using data from a survey of Jacksonville, FL residents after Hurricane Matthew, this paper examines both the factors affecting evacuation departure time choice for Hurricane Matthew and the factors associated with whether the evacuees anticipate changing their departure time for a future hurricane. The choice of departure time during disasters is a complex dynamic process and depends on the risk that the hazard represents, the characteristics of the household, and the built environment features (Hasan et al. 2013). Additional factors studied in this paper include socio-economic and demographic factors, living in a risk area, receiving evacuation notices, housing type, past hurricane experience, evacuation timing, family cohesion, hurricane information certainty, and the number of vehicles used in evacuation. Family cohesion and certainty variables are new factors to be considered in such studies. Uncertainty in this context relates to the timing and location of hurricane impact and the details of the household evacuation (e.g., destination, preparation time, route, etc.). A Cox proportional-hazards model was utilized to model the evacuation departure timing and identify the significant factors of the departure timing.

The second part of the study examines the households' anticipated consistency of departure timing for future hurricanes. Consistency would support assumptions of transferability of results from one event (in a given location) to the next, whereas anticipated changes could inform departure time range assumptions for simulation of future events. A binary logit model was used to study the binary choice of making a change in the departure timing if they relived the hurricane event.

The remainder of this paper is organized into five sections. The first section presents a selection of related literature and hypotheses investigated in this study. The second and third sections discuss the data and modeling methodology. The fourth section presents results and discussion of the findings. The final portion provides conclusions and suggestions for future research.

5.3 LITERATURE REVIEW AND HYPOTHESES

A modest number of studies focused on evacuation departure time, with most of these studies focusing on deriving empirical distributions without considering the influences of different factors (Hasan et al. 2013). These empirical distributions describe the rate of vehicles' entry to the emergency planning network (Yin, 2013). These response curves present the percentage of departures at every time interval of the planning horizon (Pel et al. 2012). A variety of shapes have been assumed for the departure time distributions. The sigmoid curve is among the most widely accepted distributions (Radwan et al. 1985) and has two main parameters: response rate and half loading time. Response rate determines the slope of the curve, where low values of this parameter leads to a more uniform departure profile (Pel et al., 2012). The time at which half of the total evacuees depart is determined by the half loading time. For realistic representation of the departure timing, these two parameters need to be calibrated (Yin, 2013). Other used distributions include the uniform distribution (Liu et al. 2008), Weibull distribution in hurricane evacuation (Lindell, 2008), Rayleigh distribution (Tweedie et al. 1986) and exponential distribution (Hobeika et al. 1994) in nuclear disaster, piece-wise linear curves in flooding (Southworth and Chin 1987), and Poisson distribution in wildfire evacuation to model the number of departing vehicles (Cova and Johnson, 2002).

Urbanik et al. (1980) divided departure time into two components: warning time and preparation time. In theory, the cumulative distribution of warning times and preparation times can be combined to produce a normalized distribution of departure times, but there are limitations (Lindell, Murray-Tuite et al. 2019). The distribution is normalized because it describes the proportion, not the absolute number, of vehicles beginning an evacuation at time t. Assuming statistical independence between warning time and preparation times, a synthetic departure time distribution can be calculated by multiplying the probability of warning receipt within a given time interval by the probability of preparing within each successive time interval (Urbanik 2000, Lindell, Murray-Tuite et al. 2019). However, Lindell, Murray-Tuite et al. (2019) stated that in practice, it can be quite challenging to construct a household distribution of departure time from the available data of warning receipt and evacuation preparation because some households evacuate before they receive an official evacuation notice. Also, constructing a synthetic departure distribution from warning diffusion and preparation time distributions requires an assumption about the correlation between warning receipt and evacuation preparation. However, it is not necessarily reasonable to have a correlation of zero, even if it is considered computationally simpler (Lindell-Murray-Tuite et al. 2019).

A few studies focused on developing explanatory models of evacuation timing decisions. Sorensen (1991) made one of the earliest attempts using path analysis for evacuation timing behavior. This method examines a set of sequential decisions made over time with evolving hurricane forecasts. The study used ordinary least squares regression to determine the relationship between departure time and other explanatory variables. Fu and Wilmot (2004) developed a sequential logit choice model, where each household makes the decision of whether to evacuate or not after reviewing the conditions of the approaching hurricane. Fu and Wilmot (2006) developed a hazard-based modeling approach to understand decisions of whether to evacuate or not and when to evacuate as a joint model. While this model provides important insight on the evacuation timing behavior, it has some limitations. First, one of the implicit assumptions of the model is that the decision of whether to evacuate and the decision of when to evacuate are made simultaneously and both decisions are influenced by the same variables. However, although these two decisions are linked, the factors and their associated influences for each kind of decision may be different. For example, the decision of whether to evacuate or not might be influenced by perception of danger to life (Hasan et al. 2013). Second, their model is estimated based on discrete time intervals with a coarse aggregation of six hour time durations. However individuals' evacuation timing decisions within this six hour interval (particularly the interval close to the hurricane landfall time) may be needed for developing efficient evacuation management strategies (Hasan et al. 2013). Most of the previous evacuation timing studies (Sorensen, 1991; Fu and

Wilmot, 2004, 2006; Lindell and Prater, 2007) included environmental, social and demographic factors and risk perception. Hasan et al. (2013) found that the variables related to household location, destination characteristics, socio-economic characteristics, and evacuation notice were key determinants of the departure time. Socio-economic and demographic characteristics such as the presence of children and living in a single family home were found to increase the likelihood of early evacuation (Sorenson, 1991). Other socio-economic and demographic characteristics such as living in mobile homes, and high educational level were found to decrease the likelihood of early evacuation (Hasan et al. 2011). On the other hand, non-significant socio-economic and demographic factors or factors with mixed findings include age, presence of senior citizens, and household size (Sorenson, 1991). Evacuation related characteristics such as receiving a mandatory evacuation order, high hurricane speed and small hurricane distance increase the early evacuation likelihood (Fu and Wilmot, 2004; Hasan et al. 2011). Other household evacuation-related characteristics including evacuation to a shelter and long evacuation preparation time decrease the likelihood of early evacuation. Yin (2013) argued that larger households, households with college graduates, and households who drive their own vehicles are more likely to engage in more travel requiring activities such as shopping activities (gasoline, medicine, food, cash withdrawal), which may lead these households to depart later. Lindell, Murray-Tuite et al. (2019) also discussed a possible reason for late evacuation of households who engage in more travel requiring activities; they argued that these households may have performed additional activities that were not on the list, which may eventually cause a delay in their evacuation process.

Much of the evidence for understanding evacuation behavior has been obtained from post-impact surveys where households are asked about their recent evacuation experience (Lindell, Murray-Tuite et al. 2019). Examining the behavior of the same households in subsequent hurricanes is one way to better anticipate future behaviors. For example, Murray-Tuite et al. (2012) studied the behavior of the same households over consecutive hurricanes (Ivan and Katrina). They examined the effect of previous decisions on later evacuations. They found that there is weak evidence on evacuating earlier in Hurricane Katrina after their Ivan evacuation experience; 27% of the respondents left at least a day earlier for Hurricane Katrina than they did for Ivan, 55% left the same number of days prior to landfall, and 18% left later. Kang et al. (2007) compared the actual behavior of evacuees from Hurricane Lili with their stated preferences about evacuation logistics collected earlier. Respondents were found to have accurate expectations about their information sources, evacuation transportation modes, number of vehicles taken, and evacuation shelter types. They also found that the mean expected evacuation time components are relatively similar to the mean actual evacuation time components.

Many factors were found to affect the evacuation decision of households; previous hurricane experience is among these factors. However, the role of previous experience is not straight forward. A recent literature review conducted for hurricane studies found no consistent relationship between experience and evacuation (Huang et al. 2016). Some studies found positive relationships, some found negative relationships, but most found no relationship. Huang et al. (2016) found that among 21 studies of household evacuation, 20% reported significant positive correlations, 10% reported significant negative correlations, and 66% reported nonsignificant correlations. These opposing findings are due to the different ways experience has been measured; these measures varied from asking general past experience questions to requiring specific information about deaths, injuries, school disruption, etc.

A special case related to experience, is the experience of " unnecessary" evacuations for a hazard that failed to struck at the warned and evacuated area. However, when households who did not evacuate were asked why they did not leave, few answered that it was due to unnecessary past evacuations. And when evacuees, including those who experience long transit times, are asked if they would do anything differently, few say they would not have evacuated (Lindell, Murray-Tuite et al. 2019). In 1985 in Panama City Beach, residents of Florida were asked to evacuate three times in the same hurricane season. The evacuation rates were basically the same in all evacuations even though the threatening storms missed in all the three cases (Baker 1991).

5.4 HYPOTHESES

A number of hypotheses were adopted for the initial selection of variables to be examined.

- *H1: Households who use more vehicles in evacuation are more likely to depart earlier.*

Murray-Tuite et al. (2012) stated that departure timing closer to the hurricane landfall often results in severe congestion, which may encourage households to travel together in congested situations. On the other hand, departing earlier to the hurricane landfall where there is less congestion may be associated with households who use more vehicles in evacuation.

- *H2: More cohesive households are more likely to depart closer to the hurricane landfall.*

Perry et al. (1981) studied the behavior of families when they receive an evacuation notice. Some families may wait for other members to return in order to evacuate together, which could delay their departure timing. Other households leave in separate groups and at different times if they were separated at the time an evacuation warning is received (Maghelal et al. 2016). In our study, family cohesion is related to decision making agreement among household members and their preference to stay together in difficult situations. More cohesive households may prefer to wait for other members to perform preparation activities, reunite, and leave together may depart closer to the hurricane landfall.

- *H3: More certainty about evacuation preparation time may lead households to depart earlier.*

According to Lindell, Murray-Tuite, et al. (2019), a delay in the evacuation departure timing occurs when households' estimated preparation time takes longer than they expected, which leads to evacuating closer to the hurricane landfall. More certainty about the time needed to prepare for evacuation leads to more accurate estimation of departure timing, thus evacuating closer to the planned departure time without preparation delays, thus leaving earlier.

- *H4: More certainty about evacuation destination may lead households to depart earlier.*

Households generally choose an evacuation destination that is more convenient for them in order to avoid the long queues of vehicles along the evacuation route (Lindell, Murray-Tuite et al. 2019). If households are certain about their evacuation destination they may choose to depart earlier, since they are certain where they are headed, and it is more convenient for them to drive without the stress of being in severely congested roads when the hurricane is approaching.

- *H5: Households who did not evacuate in previous hurricanes and the hurricanes hit are more likely to depart earlier.*

Whitehead et al. (2000) studied the effect of risk perception on the evacuation decision. They found that households perceiving greater risk about the coming hazard are more likely to evacuate. In previous hurricanes, the households who did not evacuate may have underestimated their risk or they faced too many evacuation impediments. This previous experience could have an impact on their subsequent perception of risk, which may lead them to depart earlier to avoid the risk they faced during their previous experience.

- *H6: Households who received a mandatory evacuation order are more likely to evacuate earlier.*

For most events, the majority of people do not begin to evacuate until officials issue evacuation notices (Baker 2000). Huang et al. (2016) found that the strongest predictor of a respondent evacuating (as opposed to staying) is believing they have been told by officials to evacuate. Fu and Wilmot (2004) studied the effect of receiving an evacuation notice on the likelihood of early evacuation. They found that receiving an evacuation notice increases the likelihood of early evacuation.

- *H7: Households who partially evacuate are more likely to depart closer to the hurricane landfall.*

A household is considered the basic unit for decision making in evacuations (Maghelal et al. 2016). However, households may decide to partially evacuate for various reasons, such as job responsibilities (Perry 1983), less family cohesion and conflict in decision making (Perry 1979), living in a single family dwelling home where some members of the households stay to protect their property, or having older household members in the family residence (Wilmot and Mei, 2004). Concerns about the safety of the household members, especially those who decide not to evacuate, may lead the other members to delay their evacuation (Johnson et al. 1994).

- *H8: Households who previously evacuated and the hurricane hit their community are less likely to make a change in their departure timing if they relived the hurricane event.*

Households who have previously experienced the destruction of a hurricane may have a higher perceived risk where they believe that they will experience the hazardous event and be adversely affected by it (Lindell, Murray-Tuite et al. 2019). For those households who believe they are in danger from the hazard and leaving will reduce that danger, it is less likely that they would make a change in their departure timing, assuming they made the right choice in their departure timing the previous time. Furthermore, similar departure day selections were observed for the same survey respondents after two hurricanes (Katrina and Ivan) with 55% selecting the same number of days relative to landfall (Murray-Tuite et al., 2012).

- *H9: Married households are less likely to change their departure timing if they relived the hurricane event.*

In general, married households have larger families (Maghelal et al. 2016). Yin (2013) discussed that larger households are more likely to engage in more travel requiring activities such as shopping activities (gasoline, medicine, food, and cash withdrawal). Also, married households with children may have additional trips such as picking up the children. Since these households have multiple time consuming activities, they may not change their departure timing if they relived the hurricane event, due to their full schedule prior to evacuation.

- *H10: Households who have never lived through a hurricane (prior to Hurricane Matthew) are more likely to make change in their departure timing if they relived Hurricane Matthew.*

Without prior experience, households may experiment with departure times to see if they can improve their travel experience. This type of experimentation occurs under normal conditions when someone moves to a new area or starts a new job as the commuters test the network and departure times so they arrive on time.

- *H11: Households who evacuate to homes of friends are less likely to make a change in their departure timing.*

The homes of friends and family members represent the most preferred evacuation accommodations (Lindell, Murray-Tuite et al. 2019). These locations and the approximate travel time to reach them are more familiar to the evacuees than other types of accommodations. Thus, when households decide to evacuate to a peers' residences, they are more confident about the travel time needed to reach their final destination, so if they relive the hurricane event, they would likely select a similar departure time.

5.5 DATA

After the 2016 Hurricane Matthew in the Jacksonville, Florida metropolitan area, which has a population of 1.3 million, a household survey was conducted. Four waves of surveys were distributed using Dillman et al.'s (2014) standard procedure. Each survey wave was assembled into four major blocks of questions: uncertainty factors and evacuation behaviors, social network information, intra-family decision making factors, and information sources. The survey was also made available online with an ID for each questionnaire at SurveyMonkey.com for the respondents who prefer to respond on the web. The data sample used consists of 588 respondents, of which 245 entirely evacuated households, and 30 households evacuated partially. However, due to missing data entries 241 observations were used in the study of departure timing, and 180 observations were used for the study of households' decision on making a change of later evacuation departure timing or not. Table 5-1 provides summary statistics of the selected explanatory variables.

Table 5-1. Summary Statistics of the Selected Explanatory Variables (Unweighted values)

Variable	Min-imum	Max-imum	Mean	Standard deviation
Dependent Variable				
Departure timing of households from Hurricane Matthew (Six hours intervals)	6	78	50.5	15.67
Would you change the date, time when you evacuated? (0: No; 1: Yes)	0	1	0.23	0.42
Independent Variables				
Respondent Characteristics				
Previously evacuated (0: No; 1: Yes)	0	1	0.38	0.49
Previously stayed and the hurricane hit (0: No; 1: Yes)	0	1	0.13	0.34
Never Lived a hurricane (0: No; 1: Yes)	0	1	0.30	0.46
Previously evacuated and the hurricane hit (0: No; 1: Yes)	0	1	0.13	0.32
Married (0: no; 1: yes)	0	1	0.75	0.46
Race black (0: No; 1: Yes)	0	1	0.01	0.08
Race white (0: No; 1: Yes)	0	1	0.95	0.21
Respondent Age (20 to 88 years)	20	88	59.24	13.86
Gender (0: Female; 1: Male)	0	1	0.35	0.47
Household Characteristics				
Total number of household members	1	7	2.32	1.143
Number of household members under 18 years old	0	4	0.65	1.08
Number of household members 18 - 65 years old	0	6	1.74	0.98
Number of household members over 65 years old	0	2	1.21	0.82
Number of household members with medical conditions	0	1	0.18	0.38
Income (more than 60,000 US dollars). (0: No; 1: Yes)	0	1	0.66	0.47
Family cohesion level (household members ability to cooperate in making decisions that satisfies everyone) (1-5; 1: low, 5: High)	1	5	4.50	0.81
Family cohesion level (family sticks together in difficult situations) (1-5; 1:low, 5:high)	2	5	4.73	0.60
Family cohesion level (in difficult situation, family can figure out what to do) (1-5; 1:low, 5: high)	1	5	4.46	0.84
Family cohesion level (level of household agreement about the evacuation decision from Hurricane Matthew) (1-5; 1:low, 5:high)	1	5	4.52	0.93

Home Characteristics				
Living in single family detached homes (0: no; 1: yes)	0	1	0.88	0.32
Living in mobile homes (0: no; 1: yes)	0	1	0.03	0.17
Distance to coast (miles)	0	56	10.46	12.62
Number of years in current home	0	63	14.13	12.24
Number of years in current community	0	73	19.20	16.28
Social Network				
Number of people received hurricane information from	0	10	2.50	4.47
Usefulness of information received from friends and relatives (1-5; 1: lowest, 5: highest)	1	5	3.78	1.35
Usefulness of information received from the internet (1-5; 1: lowest, 5: highest)	1	5	2.59	1.52
Concern and Certainty				
Injury concern (Risk perception); (1-5; 1: lowest, 5: highest)	1	5	2.08	1.14
Certainty about hurricane impact location (1: not certain, 5: extremely certain)	1	5	3.91	0.88
Certainty about whether they live in an evacuation zone (1: not certain, 5: extremely certain)	1	5	4.37	1.15
Certainty about time of hurricane impact (1: not certain, 5: extremely certain)	1	5	3.87	1.13
Certainty about time needed to prepare for evacuation (1: not certain, 5: extremely certain)	1	5	3.62	1.11
Certainty about when to evacuate (1: not certain, 5: extremely certain)	1	5	3.94	1.15
Certainty about evacuation destination (1: not certain, 5: extremely certain)	1	5	4.16	1.29
Certainty about evacuation route (1: not certain, 5: extremely certain)	1	5	4.29	1.05
Evacuation Details				
Evacuating to a house of friends (0: No; 1: Yes)	0	1	0.61	0.48
Evacuating to a hotel (0: No; 1: Yes)	0	1	0.33	0.47
Evacuating t a public shelter (0: No; 1: Yes)	0	1	0.00	0.06
Evacuating to another property the household owns or rents (0: No; 1: Yes)	0	1	0.00	0.09
Receiving a mandatory evacuation order (0: No; 1: Yes)	0	1	0.63	0.48
Receiving a voluntary evacuation order (0: No; 1: Yes)	0	1	0.2	0.40
Household Partially evacuated (0: No; 1: Yes)	0	1	0.060	0.244
Evacuation distance (Miles)	0	880	126.11	143.99

As can be seen in Table 2, the data sample is biased towards certain demographic characteristics relative to the population (including gender, age group, education level, marital status, and income; see Table 2). To better reflect the actual population tendencies, a method of weighting the data of the sample was needed. Rake weighting was used for this purpose. Rake weighting is basically applying weights to certain demographic characteristics in the data sample based on the overall population (Mercer et al. 2018). In this study, the rake weighting was based on three demographic variables: gender (male or female), education level (four-year college degree or lack thereof), and age group (18 through 44, 45 through 59, and 60+). These variables are not correlated, which is a requirement of the raking process. Demographic characteristics such as race were correlated with other variables, so it was removed from the rake weighting process.

Two additional demographic variables (income level, marital status) were used to test whether the raking reduced the bias outside of the raking variables themselves (Mercer et al. 2018) (Table 3). From the calculations we conclude than the bias of the evacuation departure timing dataset was reduced by 13% as shown in Table 5-2 and Table 5-3. By a similar procedure, the bias of the dataset used to model if households would make a change in their departure timing was reduced by 15%.

Table 5-2. Demographic Distributions of the Departure Timing Dataset of the 2016 Population of Jacksonville, FL

Attribute	**Category**	**Population***	**Sample**	**Bias**	**Average bias**
Age group	18 to 44	0.50	0.08	0.42	0.28
	45 to 59	0.26	0.31	0.05	
	60 or over	0.24	0.61	0.37	
Education level	no four-year college degree	0.73	0.73	0.46	0.00
	four-year college degree	0.27	0.27	0.00	

Gender	Female	0.52	0.65	0.13	0.13
	Male	0.48	0.35	0.13	
Income (annual)	less than $15,000	0.12	0.05	0.07	0.07
	$15,000 to $30,000	0.15	0.08	0.07	
	$30,000 to $45,000	0.16	0.07	0.09	
	$45,000 to $60,000	0.14	0.14	0.00	
	$60,000 to $100,000	0.24	0.26	0.02	
	over $100,000	0.19	0.40	0.21	
Marital status	not married	0.54	0.25	0.29	0.29
	Married	0.46	0.75	0.29	

*Data source: United States Census Bureau. 2016

Table 5-3. Evaluation of Bias for Departure Timing Dataset Before and After Weighting based on Marital Status and Income

Marital status	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
Not married	0.54	0.25	0.29	0.51	0.03	-0.26
Married	0.46	0.75	0.29	0.49	0.03	-0.26
Average			0.29		0.03	-0.26
Income level	**Population**	**Unweighted**	**Initial bias**	**Weighted**	**Weighted bias**	**Bias change**
1	0.12	0.05	0.07	0.10	0.02	-0.05
2	0.15	0.08	0.07	0.10	0.05	-0.02
3	0.16	0.07	0.09	0.07	0.09	0.00
4	0.14	0.14	0.00	0.14	0.00	0.00
5	0.24	0.26	0.02	0.24	0.00	-0.02
6	0.19	0.40	0.21	0.35	0.16	-0.05
Average			0.07		0.05	-0.02
	Initial bias	**Weighted bias**	**Bias change**			
Overall	0.18	0.05	-0.13			

Households were asked if they would change the date/time when they evacuated (yes or no). As shown in Table 1, 23% of the respondents answering the question indicated that they would make changes. Respondents who answered affirmatively were also asked to state their new preferred departure timing if they would change their evacuation timing; however, not enough observations were obtained to develop a model and further investigate this part.

5.6 METHODOLOGY

In this study, the evacuation departure timing was divided into six hour intervals that took place over the three day period before landfall of Hurricane Matthew (early morning, 12 am–6 am; late morning, 6 am–12 pm; afternoon, 12 pm–6 pm; and evening, 6 pm–12 am). To study the departure timing, survival analysis is used; it represents a statistical procedure that analyzes time-to-event data (Fu, 2004). Survival analysis began its application in the transportation field in the late 1980's (Fu, 2004). This type of analysis can be performed using nonparametric, semiparametric, or parametric models. For the purpose of this study, non-parametric models cannot be used since they do not estimate the effect of explanatory variables (Fu, 2004). Parametric models are used when the survival time distribution has a known parametric form. Some of the important parametric models include exponential, Weibull, gamma, log normal, log logistic, etc. (Meeker and Escobar, 1998). However, if the survival distribution is unknown and it is desirable to analyze the impact of explanatory variables, then semiparametric models are the form of model to use (Fu, 2004). This would be the case for modeling the travel demand for hurricane evacuation, where the main interest of the study is to know which variables influence the evacuation departure timing. The most popular form of semiparametric models is the Cox proportional hazards regression model (Cox, 1972). The Cox proportional hazards regression model is used in this study to model the departure timing of households in Hurricane Matthew, the underlying principles as described in (Fu, 2004) are presented below:

$$h\left(t \middle| x_{ij}\right) = h_\circ(t)\ \exp\left(\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}\right) = \ h_\circ(t)\exp\left(\sum_{j=1}^{p} \beta_j x_{ij}\right) \qquad (1)$$

where:

$h\left(t \middle| x_{ij}\right)$ is the hazard for subject *i* taking into account the influence of the covariates *xij*,

$h_\circ(t)$ is the non-negative baseline hazard function of the underlying survival distribution

when all the x variables have values of 0,

β ’s are regression coefficients,

p is the number of covariates in the model, and

x_{ij} is the value of *j*th explanatory variable for subject *i*.

The second part of this study focuses on the past experience effect on their future hurricane departure timing preference and whether they would make a change in their departure timing of later hurricanes or not. A model that could predict discrete outcomes was needed; a binary model was needed since there were only two possible outcomes (change the departure timing or not). A binary logit model is used for this part of the study since the outcome has only two possible choices. The binary logit model as described by Train (2009) is presented below:

$$P_{n1} = \frac{1}{1+e^{(V_{n2}-V_{n1})}} \qquad (2)$$

Where:

P_{n1} is the probability that outcome $n1$ will be chosen and

V_{n1} and V_{n2} are the utility expressions for the two outcomes

The selection of initial variables was based on previous evacuation departure timing literature and the previously stated hypotheses. Both a Cox proportional hazards regression model and a Binary Logit model were developed based on a number of trials where all the variables in

Table 1 were examined one by one in a forward step-wise fashion and non-significant variables were removed. Variables were considered significant if their p-values were 0.1 or less. Correlation was tested between variables, and no factors with correlation of 0.3 or more were considered in the same model (see Appendix I). The selected Binary Logit model was then tested for random parameters but no random parameter was identified, thus the fixed parameters model was preferred.

5.7 RESULTS

For the purpose of this study, two models were developed. First is the Cox proportional hazard model, that studies the departure timing as the dependent variable along with the factors affecting it. The preferred final model contains 241 observations. The Cox proportional hazard model is chi-square distributed when the model has been correctly specified (Parzen et al. 1999). Our final model has six degrees of freedom with a Chi squared value of 18.83; this indicates that our model is more than 99% significant.

Table 5-4 presents the preliminary Cox proportional hazard model. The model contains factors studied by previous literature and those presented in our hypotheses; households with higher education level and households living in mobile home are more likely to the depart earlier; which is not consistent with the previous study of Hasan et al. (2011). Other factors such as being married, which increases the likelihood of late evacuation agrees with the findings of Yin (2013); Since these households have larger families in general and much more prevacation activities than smaller households; This may lead them to depart later. Receiving a mandatory evacuation order was found to increase the chance of early evacuation as stated by Fu and Wilmot (2004). In our priliminary model, older age was found to increase the chance of early evacuation, while it was identified as not significant in Sorenson (1991) study. Hasan et al. (2011) found that evacuating to a shelter decreases the likelihood of early evacuation, which agrees with our model. Finally, our model shows that Living in a single family home increases the likelihood of early evacuation, which is consistent with Hasan et al. (2011) findings.

Table 5-5 shows the final Cox proportional hazard model results. The model contains four significant variables. Respondents who are more certain about time needed for evacuation preparation or/and who self-identify his/her race as white are more likely to depart closer to the time of hurricane landfall; these results are reasonable; since having more certainty means that the household is confident about their decision, thus they will depart in their planned time window and will not be late, so there is no need to depart earlier. Respondents who are more certain about their evacuation destinations or who previously stayed and the hurricane hit their homes are more likely to depart earlier. These results are also reasonable; and the reasons for these findings will be attributed to thorough planning and perceived risk as discussed later.

Table 55-4. Preliminary Cox hazard proportional model for evacuation departure timing

Variable description	**Coefficient**	**Standard error**
Education level	-0.007	0.0001
Mobile or manufactured home	-0.003	0.0009
Living in a single family home	-0.0001	0.0003
Married	0.001	0.0007
Age	-0.006	0.0007
Number of household members over 65	0.001	0.0001
Receiving a mandatory evacuation order	-0.0008	0.0005
Number of vehicles used in evacuation	0.005	0.0004
Concern injury	0.007	0.0004
Evacuating to a home of a friend	-0.001	0.0013
Evacuating to a public shelter	.0003	0.001
Certainty about time needed for evacuation preparation	0.002	0.0004

Never lived a hurricane event	0.1633*	0.0866
White race	0.002**	0.0009
Certainty about evacuation destination	-0.001**	0.0004
Previously Stayed and hurricane hit	-0.163**	0.086
Model Statistics		
Number of Observations	241	
Chi squared (11 degrees of freedom)	18.740	
Note: **, *⟹ Significance at 5%, 10%		

Table 5-5. Final Cox hazard proportional model for evacuation departure timing

Variable description	**Coefficient**	**Standard error**
Certainty about time needed for evacuation preparation	0.102**	0.049
White race	0.001**	0.004
Certainty about evacuation destination	-0.113**	0.049
Previously Stayed and hurricane hit	-0.181**	0.082
Model Statistics		
Number of Observations	241	
Chi squared (6 degrees of freedom)	18.83	
Note: **⟹ Significance at 5%		

In order to assess the Cox proportional hazards model, Figure 5-1 shows the observed and predicted cumulative numbers of departed households at every six hour interval (starting from 0 which represents the departure timing three days before the hurricane highest impact, to 78 which represents departing at or after hurricane landfall). The model estimates of departing households for each departure timing interval are very close to the cumulative number of observed households.

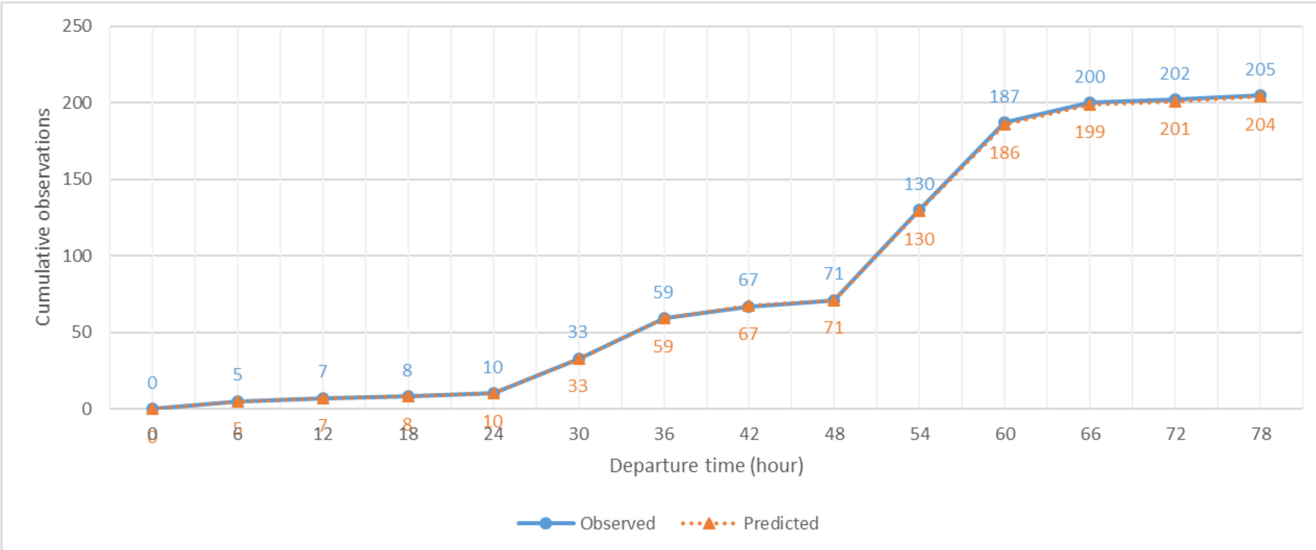

Figure 5-1 Cumulative number of households departing (observed vs. predicted)

The second developed model is the binary logit model used to study the binary decision of changing the date/time of evacuation if the households had a chance. The number of observations for this model is 180. And the estimated McFadden Pseudo R-squared is 0.122. This value shows that the current model specifications result in a model with adequate fit (McFadden 1977).

Table 5-6 shows the final binary logit final model results. The model contains five significant variables. Respondents who received a voluntary evacuation notice and/or who never lived through a hurricane prior to Hurricane Matthew are more likely to make a change to their departure day/time of evacuation. Since the evacuation notice they received is not mandatory, these households may wait and see if the hurricane is really approaching and double check if the received warnings are in place. On the other hand, households who evacuated to a home of family or friends, married households, and/or those who previously evacuated and the hurricane hit their community are less likely to make a change in their departure day/time of evacuation.

Table 5-6. Final Binary Logit model for making a change in the departure day/time

Variable description	Coefficient	Standard error
Constant	0.956*	0.529
Receiving a voluntary evacuation notice	1.611***	0.469
Evacuating to home of friends	-0.646**	0.312
Prior to hurricane Matthew the respondent evacuated and the hurricane hit his or her community	-0.612*	0.323
the respondent never lived a hurricane	0.608*	0.322
Married	-1.010**	0.325
Model Statistics		
Number of Observations	180	
McFadden Pseudo R-Squared	0.122	
Note: ***, **, * ⟹ Significance at 1%, 5%, 10%		

5.8 DISCUSSION

This section discusses the results in terms of both the hypotheses of the departure timing Cox proportional hazard model and the stated household preference about making a change in the departure timing binary logit model.

- *H1: Households who use more vehicles in evacuation are more likely to depart earlier*

This hypothesis is rejected; the number of vehicles used in evacuation was not significant in this study.

- *H2: More cohesive households are more likely to depart closer to the hurricane landfall.*

This hypothesis is rejected. Family cohesion variables were not significant in this study.

- *H3: More certainty about evacuation preparation time may lead households to depart earlier.*

This hypothesis is rejected. In our model, certainty about the time needed for evacuation preparation leads households to depart closer to the time of hurricane impact. A way to explain these findings is households who have more certainty about the preparation time needed for evacuation may be more confident leaving later or anticipate lengthier preparation requiring later departures.

- *H4: More certainty about evacuation destination may lead households to depart earlier.*

This hypothesis is supported. In this model, having more certainty about the evacuation destination has a positive effect on early evacuation because households who are certain about their evacuation destination know- for example, if they will drive through a severely congested evacuation route, or have a long drive ahead of them if their evacuation destination is far away from their residence. So, they may want to avoid congestion along the evacuation route or arrive to their far destination at their preferred time, which leads them to depart earlier.

- *H5: Households who did not evacuate in previous hurricanes and the hurricanes hit are more likely to depart earlier.*

This hypothesis is supported. In this model, households who did not evacuate in previous hurricanes and the hurricanes hit their community are more likely to depart earlier. These households may be more risk averse compared to those who did not live through a hurricane event ever or those who evacuated and the hurricane missed their community, because they may have witnessed the power of the hurricane and want to avoid any risk it may bring to themselves or their household members. Lindell, Murray-Tuite et al. (2019) also emphasized that personal distress tended to increase evacuation intentions by increasing affective risk perception.

- *H6: Households who received a mandatory evacuation order are more likely to evacuate earlier.*

This hypothesis is rejected. Almost 65% of households in our dataset indicated that they received a mandatory evacuation order. However, receiving a mandatory evacuation order is not significant in the departure timing of households.

- *H7: Households who partially evacuate are more likely to depart closer to the hurricane landfall.*

This hypothesis is rejected. Almost 6% of households in our dataset partially evacuated. However, partial household evacuation is not significant in this study.

- *H8: Households who previously evacuated and the hurricane hit their community are less likely to make a change in their departure timing if they relived the hurricane event.*

This hypothesis is supported. Households who have witnessed the destruction of a hurricane, may have a higher perceived risk. Thus, they fear the danger of the approaching hurricane and believe that leaving will reduce that danger. Since they had previous evacuation experience, they may be satisfied by their departure time selection for Hurricane Matthew and not be inclined to further experiment.

- *H9: Married households are less likely to change their departure timing if they relived the hurricane event.*

This hypothesis is supported. As discussed in the hypothesis, married households in general have larger household sizes (Wu et al. 2012), which leads them to having special arrangements and other planned trips prior to evacuation (picking up the children, shopping for medicine, getting fuel, etc.). These time consuming activities and busy schedule prior to evacuation likely leads to not changing their departure timing.

- *H10: Households who have never lived through a hurricane are more likely to make a change in their departure timing if they relived the hurricane event.*

This hypothesis is supported. Since those who never lived a hurricane have a lower experience with the evacuation network, they and may want to try different departure times in order to enhance their evacuation experience and choose the most suitable evacuation timing.

- *H11: Households who evacuate to peers' homes are less likely to make a change in their departure timing.*

This hypothesis is supported. Households who decide to evacuate to a peer's home are likely more confident about the time it takes to reach their destination due to their prior experience with the travel routes. Thus, they would choose to depart at similar timing if they relived the hurricane event.

5.9 CONCLUSIONS

This paper investigates the factors affecting evacuation departure timing. Having an accurate estimate of the departure time will allow the prediction of dynamic evacuation demand and developing effective evacuation strategies which will enhance the overall evacuation planning and management. A Cox proportional-hazards model was utilized to model the evacuation departure timing along with the significant predictors of the departure timing. The model contains four significant variables. Certainty about time needed for evacuation preparation and white race decreases the likelihood of early evacuation, while households with greater certainty about their evacuation destinations and household who previously and the hurricane hit are more likely to evacuate earlier. Certainty variables are new factors to be considered in such studies. Inclusion of such factors will help in improving understanding of human behavior during crisis events (information seeking, information sources, household members interaction, etc.), and thus uncover some aspects of the complex human decision making process. starting from the evacuation decision, trough departure time selection, accommodations (public shelter, hotel/motel, friend/relative home, etc.), evacuation destination, to evacuation travel mode and route .

Another main contribution of this paper is presenting the anticipated changes in evacuation behavior of evacuees from Hurricane Matthew. This part of the study presents the effect of households' recent hurricane experience on their preference on departure timing if they relived the hurricane event. This part of the study is among few studies that modeled the actual and stated behavior of the same evacuating households after a hurricane event. Which improves understanding and predicting households behavior; which is considered one of the significant aspects of hurricane evacuation research. A binary logit model was used to study whether households would or would not change their departure timing along with the significant factors affecting their decision. The model contains five significant variables. Respondents who received a voluntary evacuation notice and those who never lived through a hurricane prior to Hurricane Matthew are more likely to make a change to their departure day/time of evacuation. On the other hand, variables including evacuating to a home of family or friends, prior to hurricane Matthew the respondent evacuated and the hurricane hit his or her community, and being married decrease the likelihood of making departure time changes.

Departure time is one of the significant research questions that should be better understood regarding household evacuation decision. A modest number of studies focused on evacuation departure time. Though most of these studies focused on deriving empirical distributions without considering the influences of different factors (Hasan et al. 2013). This study is among the ones that have considered the effect of influencing factors on the evacuation departure timing of households.

Findings of this study provide guidance for both researchers and practitioners to take into consideration the newly introduced factors which were found significant on households decision making of the departure timing in planning and implementing successful evacuations; where emergency management agencies should take into consideration minimizing or even illuminating uncertainties within the hurricane exposed population, which will have a great impact on improving future evacuations. Future research could further investigate the effect of the certainty factors on the departure timing decision since this variable was not studied previously in this context. In particular, going further and studying the causes behind these uncertainties and uncertainty flow within the evacuation decision process would greatly enhance evacuation research. Also, the inclusion of anticipated learning behavior model of households preferred departure timing could be further studied by future research in order to better understand and predict future households evacuation behavior. In our study, almost 34% of respondents reported that they would change their departure timing if they relived the hurricane event. Such instability in the departure timing predictions are one of the main causes of evacuations implications. Thus these instabilities should be minimized in order to enhance evacuation demand estimation and develop better traffic management plans.

Acknowledgments

This work was supported by NSF grant CMMI-1520338 “Hazards SEES: Bridging Information, Uncertainty, and Decision-Making in Hurricanes using an Interdisciplinary Perspective” for which the authors are grateful. However, the authors are solely responsible for the content of this paper.

APPENDIX I

Explanatory Variables Correlation Matrix

	Certainty about preparation time	Certainty about destination	Previously stayed and hurricane hit	Race white	Voluntarily evacuation notice	Evacuating to a home of friend	Previously evacuated and hurricane hit	Never lived a hurricane	married
Certainty about preparation time	1.00								
Certainty about destination	0.27	1.00							
Previously stayed and hurricane hit	0.10	0.07	1.00						
Race white	0.05	0.04	-0.10	1.00					
Voluntarily evacuation notice	-0.03	-0.02	0.12	-0.09	1.00				
Evacuating to a home of friend	-0.01	0.36	-0.03	-0.05	0.01	1.00			
Previously evacuated and hurricane hit	0.05	0.02	-0.15	-0.10	-0.00	0.05	1.00		
Never lived a hurricane	-0.10	0.08	-0.26	0.14	-0.07	-0.03	-0.26	1.00	
married	0.03	-0.03	-0.06	0.06	0.14	-0.13	-0.03	0.09	1.00

5.10 REFFERENCES

Baker, E.J. 1991. Hurricane evacuation behavior. International Journal of Mass Emergencies and Disasters 9 (2), 287–310.

Baker, E.J. 2000. Hurricane evacuation in the United States. In Pielke, R., Jr and Peilke, R., Sr. Storms. Routledge, New York, pp. 306–319.

Cova, T., Johnson, J., 2002. Microsimulation of Neighborhood Evacuations in the Urban-Wildland Interface. Environment and Planning A 34(12), 2211 – 2229.

Cox, D.R., 1972. Regression models and life-tables. Journal of the Royal Statistical Society: Series B (Methodological), 34(2), pp.187-202.

DILLMAN, D. A., SMYTH, J. D. & CHRISTIAN, L. M. 2014. Internet, phone, mail, and mixed-mode surveys: The tailored design method (Fourth Edition), Hoboken, NJ, Wiley

Dotson, L.J., Jones, J., Schneck, D. and Sullivan, R., 2005. Development of evacuation time estimate studies for nuclear power plants. Division of Preparedness and Response, Office of Nuclear Security and Incident Response, US Nuclear Regulatory Commission.

Dow, K. and Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natural hazards review, 3(1), pp.12-18.

Fu, H., 2004. Development of dynamic travel demand models for hurricane evacuation.

Fu, H., Wilmot, C., 2004. Sequential Logit Dynamic Travel Demand Model for Hurricane Evacuation. Transportation Research Record 1882, 19-26.

Fu, H., Wilmot, C., 2006. Survival Analysis-based Dynamic Travel Demand Models for Hurricane Evacuation. Transportation Research Record 1964, 211-218.

Harrington, D.P. and Fleming, T.R., 1982. A class of rank test procedures for censored survival data. Biometrika, 69(3), pp.553-566.

Hasan, S., Mesa-Arango, R. and Ukkusuri, S., 2013. A random-parameter hazard-based model to understand household evacuation timing behavior. Transportation research part C: emerging technologies, 27, pp.108-116.

Hasan, S., Mesa-Arango, R., Ukkusuri, S. and Murray-Tuite, P., 2011. Transferability of hurricane evacuation choice model: Joint model estimation combining multiple data sources. Journal of transportation engineering, 138(5), pp.548-556.

Hobeika, A., Kim, S., Beckwith, R., 1994. A Decision Support System for Developing Evacuation Plans around Nuclear Power Stations. Interfaces 24(5), 22-35.

Huang, S-K., Lindell, M.K., Prater, C.S. 2016. Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. Environment and Behavior 48 (8), 991–1029.

JOHNSON, N. R., FEINBERG, W. E. & JOHNSTON, D. M. 1994. Microstructure and Panic: The Impact of Social Bonds on Individual Action in Collective Flight from the Beverly Hills Supper Club Fire. In: DYNES, R. R. & TIERNEY, K. (eds.) Disasters, Collective Behavior, and Social Organization. Newark, Delaware: University of Delaware Press.

Johnson, N.R., Feinberg, W.E., Johnston, D.M., 1994. Microstructure and panic: the impact of social bonds on individual action in collective flight from the Beverly Hills Supper Club Fire. In: University of Delaware press (Ed.), Disasters, Collective Behaviour and Social Organization. Newark-Delaware.

Kang, J.E., Lindell, M.K. and Prater, C.S., 2007. Hurricane Evacuation Expectations and Actual Behavior in Hurricane Lili 1. Journal of Applied Social Psychology, 37(4), pp.887-903.

Lindell, M., 2008. EMBLEM2: An empirically based large scale evacuation time estimate model. Transportation Research Part A: Policy and Practice 42(1), 140-154.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. and Baker, E.J., 2019. Large-scale evacuation. New York: Routledge.

Lindell, M.K. and Prater, C.S., 2007. Critical behavioral assumptions in evacuation time estimate analysis for private vehicles: Examples from hurricane research and planning. Journal of Urban Planning and Development, 133(1), pp.18-29.

Liu, Y., Okada, N., Takeuchi, Y., 2008. Dynamic Route Decision Model-based Multi-agent Evacuation Simulation - Case Study of Nagata Ward, Kobe. Journal of Natural Disaster Science 28, 91-98.

Maghelal, P., Peacock, W.G. and Li, X., 2016. Evacuating together or separately: factors influencing split evacuations prior to Hurricane Rita. Natural Hazards Review, 18(2), p.04016008.+

McFadden, D., 1977. Quantitative methods for analyzing travel behavior of individuals: some recent developments. Berkeley: Institute of Transportation Studies, University of California.

Meeker, W.Q., Escobar, L.A. and Lu, C.J., 1998. Accelerated degradation tests: modeling and analysis. Technometrics, 40(2), pp.89-99.

Mercer, A., A. Lau, and C. Kennedy, For Weighting Online Opt-In Samples, What Matters Most? Pew Research Center, 2018.

MERCER, A., LAU, A. & KENNEDY, C. 2018. For Weighting Online Opt-In Samples, What Matters Most? Pew Research Center

Murray-Tuite, P., Yin, W., Ukkusuri, S.V. and Gladwin, H., 2012. Changes in evacuation decisions between Hurricanes Ivan and Katrina. Transportation research record, 2312(1), pp.98-107.

Parzen, M. and Lipsitz, S.R., 1999. A global goodness-of-fit statistic for Cox regression models. Biometrics, 55(2), pp.580-584.

Pel, A.J., Bliemer, M.C. and Hoogendoorn, S.P., 2012. A review on travel behaviour modelling in dynamic traffic simulation models for evacuations. Transportation, 39(1), pp.97-123.

PERRY, R. W. 1983. Population Evacuation in Volcanic Eruptions, Floods and Nuclear Power Plant Accidents: Some Elementary Comparisons. Journal of Community Psychology, 11, 36-47.

Perry, R.W., 1979. Evacuation decision-making in natural disasters. Mass emergencies, 4(1), pp.25-38.

Perry, R.W., Greene, M.R. 1983. Citizen Response to Volcanic Eruptions. New York: Irvington.

Radwan, A., Hobeika, A., Sivasailam, D., 1985. A computer simulation model for rural network evacuation under natural disasters. ITE Journal 55 (9), 25–30.

Sorensen, J.H., 1991. When shall we leave? Factors affecting the timing of evacuation departures. International journal of mass emergencies and disasters, 9(2), pp.153-165.

Southworth, F., Chin, S.-M., 1987. Network evacuation modelling for flooding as a result of dam failure. Environment and Planning A 19(11), 1543 – 1558.

Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

Tweedie, S., Rowland, J., Walsh, S., Rhoten, R., Hagle, P., 1986. A Methodology for Estimating Emergency Evacuation Times. The Social Science Journal 23(2), 189-204.

UCLA: Statistical Consulting Group, 2013. What statistical analysis should I use? UCLA, Los Angeles, CA.

UNITED STATES CENSUS BUREAU. 2018. 2016 American Community Survey (gender, education, age, marital status, and income levels for Jacksonville, FL) [Online]. [Accessed]

Urbanik, T. 2000. Evacuation time estimates for nuclear power plants. Journal of Hazardous Materials 75 (2), 165–180.

Urbanik, T., Desrosiers, A., Lindell, M.K., Schuller, C.R. 1980. An Analysis of Techniques for Estimating Evacuation Times for Emergency Planning Zones, NUREG/CR-1745. US Nuclear Regulatory Commission, Washington, DC.

Whitehead, J.C., Edwards, B., Van Willigen, M., Maiolo, J.R., Wilson, K. and Smith, K.T., 2000. Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behavior. Global Environmental Change Part B: Environmental Hazards, 2(4), pp.133-142.

Wu, H.C., Lindell, M.K. and Prater, C.S., 2012. Logistics of hurricane evacuation in Hurricanes Katrina and Rita. Transportation research part F: traffic psychology and behaviour, 15(4), pp.445-461.

Yin, W., 2013. An Agent-based Travel Demand Model System for Hurricane Evacuation Simulation (Doctoral dissertation, Virginia Tech).

CHAPTER SIX

CONCLUSIONS

6.1 Contributions

This dissertation investigates the evacuate/stay decision, household vehicle usage in evacuation, and the determinants of departure timing and the evacuation learning experience from Hurricane Matthew. Regarding the evacuate/stay decision, this study is among the few that have considered partial household evacuation, using multinomial logit models with and without random parameters, the latter of which are used to account for the heterogeneity of the parameter effects.

The inclusion of partial household evacuation suggests that the effects of several of the factors (e.g., living in a mobile home, concern about injuries) that have long been believed to increase the likelihood of evacuating are more nuanced than previously believed as they decrease the likelihood of none of the household evacuating but increase the likelihood of partial household evacuation while decreasing the likelihood of complete household evacuation. This suggests that the evacuation decision making process is complex and opinions may vary within a household. Split household decisions impacts both the total number of evacuees and the total number of evacuating vehicles, although the latter needs further investigation for future evacuations.

The significance of studying household vehicle usage comes from the need to anticipate the total number of vehicles used in an evacuation to properly plan traffic management and mitigation strategies as well as fuel supplies. Current studies present a range of evacuating household vehicle numbers, but this could lead to a vast difference when taking into account the total number of evacuating households. This study contributes to the relatively small body of literature examining factors influencing the number of household vehicles used in an evacuation. It is among the first to use a zero truncated Poisson model in the evacuation context. The findings of this study provide deeper insight for evacuation managers about indicators to be considered while preparing more comprehensive evacuation plans. This could enhance evacuation demand estimation and improve evacuation traffic management plans. The findings of this study will be further utilized by other team members working on the same project in the overall demand estimation for evacuation from Hurricane Matthew.

This study also investigates the factors affecting evacuation departure timing, in order to better understand the complex dynamic decision of departure timing. This study identifies factors associated with households' choice of departure time, which will allow the prediction of dynamic evacuation demand and developing effective evacuation strategies which will eventually enhance the overall evacuation planning and management. A Cox proportional-hazards model was utilized to study the evacuation departure timing along with its significant predictors. Our final model contains four significant variables. Three of them are related to uncertainty and family cohesion and decision making agreement, which, as discussed earlier, are among the important newly introduced variables to such studies.

This study also explores the effect of households' recent hurricane experience on their preference on departure timing if they relived the hurricane event. This part of the study is among the few studies that modeled the actual and stated behavior of the same evacuating households after a hurricane event. This improves understanding and predicting of households' behavior. A binary logit model was used to study whether households would or would not change their departure timing along with the significant factors affecting their decision. The model contains five significant variables related to the type of evacuation order, evacuation destination, and prior hurricane experience. The inclusion of anticipated learning behavior model of households preferred departure timing could be further studied by future research in order to better understand and predict future households evacuation behavior. In our study, almost 34% of respondents reported that they would change their departure timing if they relived the hurricane event. Such instability in the departure timing predictions are one of the main causes of evacuation challenges.

This dissertation was based on a post-hurricane survey to the residents of Jacksonville, Florida, and the models introduced are specifically for this hazard. Some of our explored factors were found to match and confirm the findings of previous literature (e.g., The negative effect of married households on the evacuation decision (Wilmot and Mei (2004)), the positive effect of living in mobile homes on evacuation (Hasan et al. (2011)), the positive effect of risk perception on evacuation (Perry (1979)), the positive effect of being married on the number of household vehicles used in evacuation (Wu et al. (2012)), etc.,). Which means that the effect of these listed factors could be applied to different strength hurricanes and in different areas; since they have similar outcomes compared to previous literature. While other factors were found to have different findings that do not support previous literature when tested in our models. Our findings include the negative effect of risk perception on full household evacuation, the negative effect of having more certainty about hurricane impact location on full household evacuation, the negative effect of late morning departure timing on the number of vehicles used in evacuation, the non-significance of using more vehicles on departure timing, etc.,. These factors may need further exploration by different studies in different places and for different hazards in order to confirm whether they could be transferred to other hurricanes, areas, and for different hazards. Especially those that were found to have different findings when partial evacuation was taken into account.

Findings of this study provide guidance for both researchers and practitioners to take into consideration the newly introduced factors (certainty factors, partial household evacuation, family cohesion) in planning and implementing successful evacuations. Emergency management agencies should take into consideration minimizing or even illuminating uncertainties within the hurricane exposed population, which will lead to having people evacuate safely to their destinations by travelling on convenient evacuation routs and determining the best departure timing and the most efficient number of evacuating vehicles. since they have more certainty about the upcoming threat, what to do, and when to act, which will have a great impact on improving future evacuations.

6.2 Future Directions

Future research could further explore partial household evacuation. In particular, researchers could investigate how differences of opinion within the household are resolved into an outcome, whether split, all stay, or all evacuate. Additionally, the composition of the staying and evacuating groups for split households could be explored to better understand the needs of those who remain behind and those who shelter elsewhere. Future research could also further explore partial household evacuation as an indicator of the number of household vehicles used in evacuation, and the departure timing of the evacuating households. This variable was not studied previously in this context and had mixed significance in our study regarding the number of evacuating vehicles (significant in the individual variable model but non-significant in the multivariable model). It is important to better understand the factors leading a household to partially or fully evacuate since these factors could affect all the following evacuation logistics. Also, inclusion of the anticipated learning behavior modeling of households' preferred departure timing could be further studied to better understand and predict future households' evacuation behavior, which will eventually enhance evacuation demand estimation used in developing better traffic management plans.

The transferability over time of the binary choice of changing the departure timing if household members relived the hurricane event could be further explored by future researchers to see if the stated preference on changing the evacuation departure timing of Jacksonville residents would match their actual evacuation behavior in later hurricanes.

Throughout this dissertation, additional data items would have helped the researchers in their study, such as inclusion of the total number of owned vehicles by the household in addition to the number of evacuating vehicles. Other potentially useful data includes the number of evacuating children, older household members, and household members with medical needs. Inclusion of data about non-traditional households (e.g., roommates) would also benefit in this research topic. Future researchers are advised to obtain these additional data which will benefit them in their research.

Appendix I

Statistics of The General Data Sample

Variable	Minimum	Maximum	Mean	Standard deviation
Number of household vehicles used in evacuation	1	4	1.34	0.653
Household Partially evacuated (0: No; 1: Yes)	0	1	0.060	0.244
Departure timing of households from Hurricane Matthew (Six hour units of time)	0	78	50.5	15.67
Would you change the date, time when you evacuated? (0: No; 1: Yes)	0	1	0.23	0.42
Respondent Characteristics				
Previously evacuated (0: No; 1: Yes)	0	1	0.53	0.51
Married (0: no; 1: yes)	0	1	0.72	0.45
Race black (0: No; 1: Yes)	0	1	0.00	0.00
Race white (0: No; 1: Yes)	0	1	0.91	0.258
Respondent Age (20 to 92 years)	20	92	57.93	14.10
Gender (0: Female; 1: Male)	0	1	0.41	0.45
Household Characteristics				
Total number of household members	1	7	2.31	1.23
Number of household members under 18 years old	0	6	0.61	1.16
Number of household members 18 - 65 years old	0	6	1.60	0.92
Number of household members over 65 years old	0	2	1.23	0.89
Number of household members with medical conditions	0	1	0.18	0.33
Income (more than 60,000 US dollars). (0: No; 1: Yes)	0	1	0.67	0.47
Family cohesion level (1-5; 1: low, 5: High)	1	5	4.51	0.79
Home Characteristics				
Living in single family detached homes (0: no; 1: yes)	0	1	0.89	0.30
Living in mobile homes (0: no; 1: yes)	0	1	0.03	0.19
Distance to coast (miles)	0	56	10.69	12.32
Number of years in current home	0	63	14.17	12.64
Number of years in current community	0	74	19.17	16.24
Concern and Certainty				
Injury concern (Risk perception); (1-5; 1: lowest, 5: highest)	1	5	2.25	1.24
Certainty about hurricane impact location (1: not certain, 5: extremely certain)	1	5	3.70	1.16
Certainty about whether they live in an evacuation zone (1: not certain, 5: extremely certain)	1	5	4.42	1.17
Certainty about time of hurricane impact (1: not certain, 5: extremely certain)	1	5	3.92	1.14
Certainty about time needed to prepare for evacuation (1: not certain, 5: extremely certain)	1	5	3.88	1.25

Certainty about when to evacuate (1: not certain, 5: extremely certain)	1	5	3.89	1.10
Certainty about evacuation destination (1: not certain, 5: extremely certain)	1	5	4.13	1.31
Certainty about evacuation route (1: not certain, 5: extremely certain)	1	5	4.30	1.09
Evacuation Details				
Evacuation on the day of highest impact (0: No; 1: Yes)	0	1	0.03	0.23
Evacuation 1 day before highest impact (0: No; 1: Yes)	0	1	0.42	0.22
Evacuation 2 days before highest impact (0: No; 1: Yes)	0	1	0.37	0.49
Evacuation 3 days before highest impact (0: No; 1: Yes)	0	1	0.17	0.37
Evacuation timing (from midnight to 6 am) (0: No; 1: Yes)	0	1	0.06	0.20
Evacuation timing (6 am to noon). (0: No; 1: Yes)	0	1	0.35	0.47
Evacuation timing (noon to 6 pm). (0: No; 1: Yes)	0	1	0.30	0.44
Evacuation timing (6 pm to midnight). (0: No; 1: Yes)	0	1	0.13	0.34
Evacuation distance (Miles)	0	880	125.45	145.47

Appendix II

Demographic distributions of the general data sample and the 2016 population of Jacksonville, FL

Attribute	**Category**	***Population**	**Sample**
Age group	18 to 44	0.50	0.13
	45 to 59	0.26	0.32
	60 or over	0.24	0.55
Education level	no four-year college degree	0.73	0.29
	four-year college degree	0.27	0.71
Gender	female	0.52	0.63
	male	0.48	0.37
Income (annual)	less than $15,000	0.12	0.04
	$15,000 to $30,000	0.15	0.08
	$30,000 to $45,000	0.16	0.07
	$45,000 to $60,000	0.14	0.15
	$60,000 to $100,000	0.24	0.27
	over $100,000	0.19	0.39
Marital status	not married	0.54	0.27
	married	0.46	0.73

*Population data source: (United States Census Bureau, 2018)

Appendix III

Evacuation notice type received * evacuation decision Crosstabulation

	Full household evacuation(%)	Partial household evacuation	No household evacuation	Total
Mandatory evacuation notice	152	15	24	191
Voluntary evacuation order	52	7	47	106
Did not receive any notice	28	8	154	190
Don't know/not sure	9	0	14	23
Total	241	30	239	510